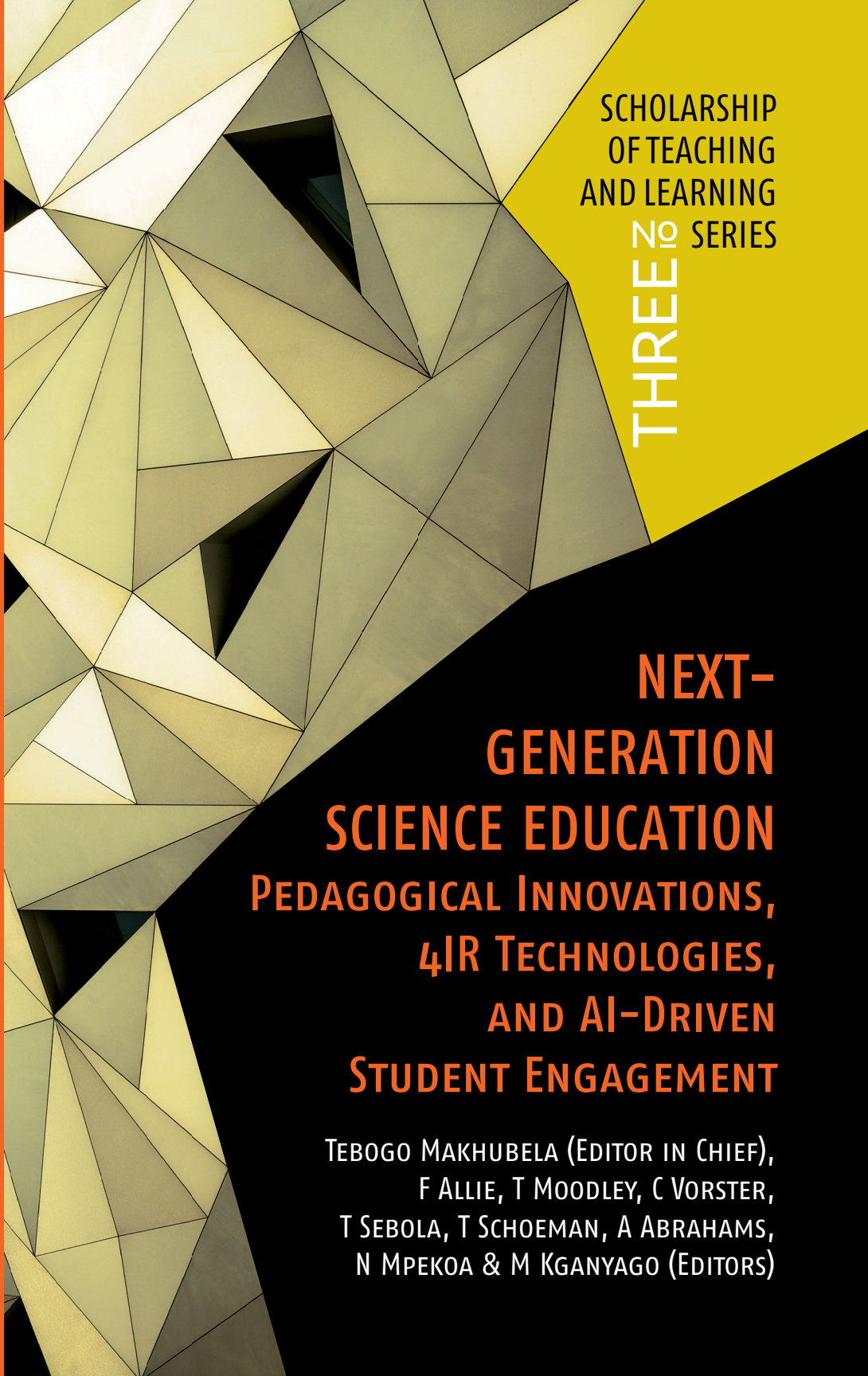


SCHOLARSHIP OF TEACHING AND LEARNING

No THREE SERIES

# NEXT-GENERATION SCIENCE EDUCATION

## Pedagogical Innovations, 4IR Technologies, and AI-Driven Student Engagement

Tebogo Makhubela (Editor in Chief),
F Allie, T Moodley, C Vorster,
T Sebola, T Schoeman, A Abrahams,
N Mpekoa & M Kganyago (Editors)



# Next-Generation Science Education

## Pedagogical Innovations, 4IR Technologies, and AI-Driven Student Engagement

Volume edited by:
Tebogo Makhubela (Editor in Chief), Farhahna Allie, Tevin Moodley, Clarisa Vorster, Tendani Sebola, Thea Schoeman, Adrian Abrahams, Noluntu Mpekoa, Mahlatse Kganyago



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# Acknowledgments

The editors extend their sincere gratitude to all the chapter contributors who made this volume possible. As scientists and researchers, the authors embraced the opportunity to step beyond their primary research disciplines to critically reflect on their teaching practices, learning environments, and educational experiences. Their willingness to engage in scholarly reflection and share innovative approaches to teaching has enriched this volume and contributed meaningfully to ongoing efforts to enhance Science education in higher education.

We acknowledge with appreciation Professor Sehaam Khan, the Deputy Vice-Chancellor: Academic of the University of Johannesburg, for establishing the Scholarship of Teaching and Learning (SoTL) Book Series under UJ Press, thereby creating an important platform for advancing educational scholarship across the institution.

We are equally grateful to the Faculty of Science for championing the conception and development of this book. The support, encouragement, and financial commitment provided by Professor Annah Moteetee, the Dean, and Professor Kulsum Kondiah, the Vice-Dean: Teaching and Learning, were instrumental in bringing this project to fruition.

Our sincere thanks are extended to Wikus van Zyl and the editorial team at UJ Press for their guidance, professionalism, and support throughout the publication process. Their expertise and commitment have been invaluable in transforming this manuscript into a published volume.

Finally, we gratefully acknowledge the anonymous peer reviewers whose thoughtful and constructive feedback strengthened the quality of the chapters. Their careful evaluations, critical insights, and recommendations helped the authors to refine their contributions and enhance the overall scholarly quality of this publication.

It is our hope that this volume will contribute to ongoing conversations about excellence, innovation, and student-centred teaching in Science education, while inspiring educators to continually reflect upon and improve their practice.

# Biographies

## Abrahams, Adrian

Dr Adrian Abrahams is a Senior Lecturer at the University of Johannesburg with seven years' teaching experience in higher education. He is currently lecturing at the 3rd year, Advanced Diploma, and Honours levels, specialising in Microbial Biochemistry, Molecular Genomics, and Biotechniques. Dr Abrahams has contributed to curriculum development and programme coordination, ensuring that course content remains current and engaging. He is committed to enhancing student learning through innovative teaching methods, including digital learning initiatives and hands-on laboratory instruction, that foster active student engagement. His approach to teaching is centred on fostering a supportive and inclusive learning environment where every student feels valued and empowered to succeed. He believes that meaningful student engagement arises from creating connections that go beyond content delivery — by showing genuine care, compassion, and empathy towards each learner's unique experiences and challenges. By cultivating empathy and compassion in his approach to teaching, he aims to inspire students to not only grasp scientific concepts but also to develop confidence, resilience, and a lifelong love of learning. His goal is to nurture curiosity and critical thinking while supporting students through challenges with patience and encouragement, fostering a classroom community where everyone can thrive.

## Allie, Farhahna

Dr Farhahna Allie is a Senior Lecturer in the Department of Biochemistry at the University of Johannesburg (UJ). She has more than 10 years' experience in higher education, teaching undergraduate and postgraduate students in Molecular Biology, Genetics and Biochemistry. Her teaching includes both theoretical and laboratory-based learning, with a strong emphasis on developing scientific thinking and practical skills. She supervises Honours, Master's and PhD students and supports curriculum

development and assessment design. She has served as Deputy Head of Department: Research in the Department of Biochemistry and as the STEM MentHER Division Manager at UJ, contributing to academic leadership, mentorship and student development. Her teaching practice follows a holistic, student-centred approach that promotes inclusive learning, critical thinking and active engagement. She has developed digital learning initiatives and gamified activities to improve engagement and support diverse learning needs. She also co-developed an AI-supported learning platform, LearnBridge, to give students accessible academic support beyond the classroom. Dr Allie is committed to learning environments that encourage collaboration, curiosity, scientific enquiry and the confidence to solve real-world problems. Her interest in the Scholarship of Teaching and Learning centres on inclusive teaching and educational technology. Her work has been recognised through the Faculty of Science Teaching Excellence Award.

## Chikore, Tichaona

Dr Tichaona Chikore served as a contract Lecturer in the private higher education sector and in the Department of Mathematics and Applied Mathematics at the University of Johannesburg, South Africa. He has over five years of higher education teaching experience, delivering undergraduate modules including Precalculus, Calculus, Algebra, Mathematics for Teachers, and Mathematics for business disciplines such as Retail and Marketing. His teaching extends to postgraduate supervision, where he has mentored Master's and PhD students in applied mathematical modelling. He has also participated in coordinating the recruitment, training, and mentoring of departmental tutors to enhance student learning. Dr Chikore has contributed to curriculum development within the College of Business and Economics at the University of Johannesburg and through Siyavula, a South African educational technology organisation, where he supported the development of curriculum-aligned high school Mathematics content and assessment resources. His educational practice includes assessment design, digital learning technologies, online teaching resources, and active

student engagement. Beyond the classroom, he has delivered professional training in quantitative methods, data analytics, and monitoring and evaluation for postgraduate Researchers and industry professionals. His interests include innovative teaching, technology-enhanced learning, curriculum development, and the Scholarship of Teaching and Learning to improve student success in quantitative disciplines.

## Coulter, Duncan

Prof Duncan Anthony Coulter has been at the University of Johannesburg (by way of its precursor institution the Rand Afrikaans University) since 2001. After a brief digression into the computerised psychometric assessment industry in the United Kingdom in 2005, he returned to the now University of Johannesburg as a permanent academic staff member in 2007. His research interests have focused on the intersection of the abstractions of biological processes and artificial intelligence in the context of multi-agent systems. He implemented the creation of several academic programmes. Specifically, the Artificial Intelligence and Cyber Security specialisation BSc Honours degrees, the Artificial Intelligence BSc undergraduate specialisation, the Intelligent Systems Development with TensorFlow Short Learning Programme, and the new BSc (Computer Science and Informatics) Extended degree programme, including new modules in Computational Thinking and System Administration and Automation. He has recently concluded a term as Head of Department for the Academy of Computer Science and Software Engineering within the Faculty of Science but is greatly relieved to be able to focus on academic matters once again.

## Green, Ezekiel

Prof Ezekiel Green is a Professor of Microbiology in the Department of Biotechnology and Food Technology at the University of Johannesburg, South Africa. He has more than 25 years' experience in higher education, having begun his academic career at the University of Venda in 2000, joined the University of Fort Hare in 2007, and the University of Johannesburg in 2017. He has taught undergraduate and

postgraduate courses in Microbiology, Biotechnology, Molecular Biology, Microbial Genetics, Environmental Microbiology, and other laboratory-based disciplines. Professor Green has graduated more than 50 Honours students, 32 Master's students, and 16 Doctoral students, and has supervised three postdoctoral Researchers. He has provided academic leadership through curriculum design and review, including the development of the Advanced Diploma in Biotechnology curriculum following the replacement of the BTech qualification, and the Honours in Biotechnology curriculum at the University of Johannesburg. He has also contributed to assessment moderation, programme review, quality assurance, and undergraduate module coordination. His teaching is informed by Humanism, Constructivism, and Connectivism, fostering student-centred learning, active engagement, authentic laboratory experiences, collaborative knowledge construction, and the meaningful integration of digital technologies. The perspectives presented in his chapter are grounded in his extensive experience of creating inclusive learning environments that develop critical thinking, scientific enquiry, and lifelong learning.

## Hlongwani, Caroline

Ms Caroline Hlongwani is a Geoscience Educator and Researcher with a strong interest in Earth Sciences as well the Scholarship of Teaching and Learning (SoTL). In particular, Ms Hlongwani has a keen interest in creating and developing inclusive and effective learning environments for undergraduate students within the field of Geosciences. Her teaching experience spans from classroom, laboratory, and field-based Geology education, with a focus on supporting first-year students as they transition into higher education, and cultivate the cognitive and disciplinary modes of thinking necessary for academic success. In the South African higher education system, students with different academic backgrounds join universities, in addition to them having little or no knowledge of field-based learning. Consequently, her teaching career has been focused on designing pedagogical interventions to bridge formal and experiential learning environments. These pedagogical interventions include stage learning or guided

learning approach, field-based and laboratory-informed teaching approaches that are aimed at enabling students to interpret various geological phenomena when encountered in the field. The above experiences informed this book chapter, which reflects on the design, implementation, and evaluation of teaching strategies aimed at improving student engagement, knowledge transfer, and learning outcomes during a first-year Geology field school.

## James, Jacinda

Dr Jacinda James is a Technical Manager in the Department of Biochemistry the University of Johannesburg (formerly Rand Afrikaans University). She has been involved for over 26 years in higher education teaching and learning in both undergraduate and postgraduate education, particularly in laboratory-based teaching and practical skills development. Her teaching focuses primarily on the undergraduate Biochemistry practical for Biochemical Techniques and Enzymology and Integrated Metabolism. Her responsibilities include the design and delivery of practical sessions, the development of study guides and assessments, laboratory coordination, and student support. She is committed to fostering scientific curiosity, critical thinking, and student engagement through hands-on learning and the effective use of digital learning platforms. Dr James has supervised and co-supervised Honours research projects, co-supervised an MSc student, and serves as an external moderator for undergraduate and postgraduate modules at the University of Venda. She has received multiple institutional awards, including the Faculty of Science Service Beyond Call of Duty Award twice and several Orange Ribbon Awards for exceptional service. She also serves on Faculty and University Teaching and Learning committees and has represented the Faculty of Science on the University Timetables Committee since 2015.

## Kganyago, Mahlatse

Dr Mahlatse Kganyago is a Senior Lecturer in Remote Sensing and GIS in the Department of Geography, Environmental Management, and Energy Studies at the University of Johannesburg. He teaches across undergraduate and postgraduate levels, with a focus on

Geo-Informatics, GIS, Remote Sensing, Cartography, Spatial Analysis, and Applied Geospatial technologies. His teaching includes Geography 3A Geo-Informatics, Geo-Informatics I, Geo-Informatics II, and short learning programmes such as Introduction to GIS for Teachers and Applied GIS and Remote Sensing. His teaching practice is grounded in experiential, student-centred learning, linking theory to practical exercises, field-based and laboratory-style geospatial work, and real-world African environmental contexts. He uses blended learning approaches, including learning management systems, instructional videos, exemplars, and digital tools such as ArcGIS, QGIS, Field Maps, Survey123, and QField. He is also involved in curriculum and course material development, module coordination, and professional short-course design for government and industry. He supervises Honours, Master's, and Doctoral students in Geography, GIS, and Remote Sensing, and is particularly interested in inclusive, technology-enhanced teaching and postgraduate supervision.

## Kondiah, Kulsum

Prof Kulsum Kondiah is an Associate Professor and Vice Dean of Teaching and Learning in the Faculty of Science at the University of Johannesburg (UJ). With over 15 years' experience in higher education, she has taught Biochemistry, Microbiology, Immunology, Biotechnology and Bioentrepreneurship at all levels. She is intentional about designing authentic, enquiry-driven learning experiences to foster critical thinking, scientific reasoning, and student engagement. Her interest in the Scholarship of Teaching and Learning is driven by evidence-informed practices in curriculum development, academic programme leadership, staff development, and the integration of innovative teaching approaches, such as digital learning experiences. Her contributions to teaching excellence, student success, and graduate preparation have been recognised within and outside of UJ; the most recent being the *Mail & Guardian Power of Women in Education Award* (2025). Alongside her educational leadership, Prof Kondiah maintains an active research programme in nanotechnology for waterborne pathogen

surveillance. She has supervised 22 Master's and 3 PhD graduates to completion, published her research in internationally accredited journals and holds an international patent.

## Koorsen, Gerrit

Dr Gerrit Koorsen is a Senior Lecturer in the Department of Biochemistry at the University of Johannesburg, where he has taught in higher education since 2008. His undergraduate teaching centres on foundational biochemistry through the module *Principles of Biochemistry*, while at Honours level, he lectures in protein biochemistry, structural biology, and bioinformatics, which are his main research fields. In the educational space, he co-supervised a Doctoral study on augmented reality (AR) in biochemistry higher education. He serves on his department's curriculum development committee and has presented workshops on AR and virtual reality in teaching to education students at several South African higher education institutions. His teaching practice is grounded in the scholarship of teaching and learning, with a particular focus on educational technology. He has received three Teaching Innovation Grants from the UJ Division for Teaching Excellence, supporting the development of AR applications for 3D molecular visualisation and the LearnBridge AI tutoring platform that informs his chapter. In 2024, he received the Faculty of Science Teaching Award. He maintains a keen interest in the integration of artificial intelligence into teaching and learning in the molecular sciences.

## Kwenda, Phyllis

Dr Phyllis R. Kwenda is a post-doctoral research fellow (PDRF) specialising in solid waste management, public health data analytics, and community resilience at the University of Johannesburg. With a PhD background in bioresources, bioresource systems, and biotechnology, her research operates at the intersection of environmental safety, public health safety, waste management, and applied statistics, specifically focusing on mitigating socio-environmental vulnerabilities in southern Africa. She has 10 peer-reviewed publications, which utilised rigorous quantitative research designs and cross-sectional

community surveys to address critical sanitation, waste management, and infrastructure challenges. Her expertise includes solid waste management, mixed-methodology research design, and field research to promote data-driven learning and provide information for future public health Researchers.

## MacRoberts, Robyn

Dr Robyn MacRoberts is an early-career Geology Lecturer and Researcher in the Department of Geology at the University of Pretoria. She teaches a broad range of subjects, including Stratigraphy, introductory South African Geology, Geochronology (age dating), Metamorphic Petrology, and Structural Geology. Her teaching philosophy is centred on experiential and field-based learning, with a strong emphasis on equipping students with practical geological skills such as rock identification, geological structure recognition, geological mapping, and compass use. With close to 10 years' experience working with students from first-year undergraduate to MSc level, Dr MacRoberts has served as a teaching assistant, Lecturer, and field trip leader. She has extensive experience facilitating field-based teaching and is passionate about creating engaging outdoor learning environments that encourage confidence, curiosity, and active participation. Her approach focuses on developing innovative teaching strategies that make the field classroom more accessible, enjoyable, and effective for students at all levels of study. Through her commitment to student-centred learning, she strives to cultivate both technical competence and a lasting enthusiasm for the geosciences.

## Makhubela, Tebogo

Dr Tebogo Makhubela is a Senior Lecturer in the Department of Geology at the University of Johannesburg. He holds a PhD in Geology and has more than 12 years' higher education teaching experience across undergraduate, Honours, and Master's programmes. His teaching portfolio spans a diverse range of subjects, including Geology, Field Techniques, Environmental Geology, Historical and Economic Geology, Mineralogy, and Hydrogeology. As Module Coordinator for Geology / Field

Techniques, Dr Makhubela has a particular interest in experiential and field-based learning. His teaching innovations include integrating laboratory-based materials, such as thin section photomicrographs and polished hand specimens, into field teaching environments to strengthen the connection between classroom and out-of-classroom learning. He has also fostered industry engagement by incorporating guest lectures from practicing professionals into the curriculum. Dr Makhubela has supervised 12 Honours projects, five Master's students, and two PhD candidates. His growing Scholarship of Teaching and Learning (SoTL) portfolio includes peer-reviewed journal publications, conference contributions, and educational innovation outputs focused on student engagement and authentic learning in the geosciences. His educational practice is centred on creating meaningful learning experiences that bridge theory, practice, and professional application.

## Meijboom, Reinout

Prof Reinout Meijboom was born and raised in the Netherlands. He studied Chemistry at the University of Groningen, where he completed his MSc research. Subsequently, he moved to Cape Town to pursue his PhD in Organometallic Chemistry. Following his PhD, he pursued a post-doctoral fellowship at the then Rand Afrikaans University and the University of the Free State. Reinout took up the position of Senior Lecturer at the University of Johannesburg in 2008 and rose through the ranks at UJ to full Professor. His current research interests are the digitisation of Chemistry. This includes the design and construction of robotic systems for Synthetic Chemistry, high-throughput experimentation, Flow Chemistry, Data Science, and AI optimisation of reaction conditions. This completely new field of Chemistry necessitates that the principles and ideas be introduced as early as possible in the undergraduate curriculum. As a result, a large amount of effort is directed towards the frugal construction of robotic units and the development of educational materials on Digital Chemistry. Several educational papers have already been published on Frugal Flow Chemistry and Robotic Synthesis. The overall aim is to introduce Digital Chemistry at low cost in resource-restricted environments to enable African Researchers.

## Molelekoa, Tumisi

Dr Tumisi Molelekoa is a Senior Lecturer and Researcher in the Department of Biotechnology and Food Technology at the University of Johannesburg. He teaches Food Biochemistry and Food Technology to undergraduate and postgraduate students and serves as Deputy Director of the Centre for Innovative Food Research and Deputy Head of Department for Teaching and Learning. He is also a BRICS Young Scientist and contributed to the think tank that developed the 2024 Energy Outlook on Sustainability. He is passionate about teaching and student success. His work explores the integration of everyday food experiences into science education to improve students' understanding of chemistry concepts, engagement, and academic performance. He adopts a learner-centred teaching approach, believing that students learn most effectively when they are encouraged to actively explore and interact with their environments. His teaching philosophy is guided by constructivist principles and incorporates humour and gamification to create engaging and meaningful learning experiences. His commitment to excellence in teaching has been recognised through several prestigious awards, including the University of Johannesburg Faculty of Science Emerging Teacher Award in 2023 and the Vice-Chancellor's Distinguished Award for the Promising Young Teacher in 2025. Guided by Voltaire's belief that "there is no problem that can stand the assault of sustained thinking," he continually strives for excellence in teaching, research, leadership, and personal growth.

## Modley, Lee-Ann

Prof Lee-Ann Sadè Modley is an Associate Professor in the Department of Geography, Environmental Management and Energy Studies at the University of Johannesburg. She holds a PhD in Environmental Management and has over 12 years' teaching experience in higher education. Her teaching portfolio spans undergraduate and postgraduate programmes in Environmental Management, Sustainability, Water Resource Management, Environmental Governance, Environmental Impact Assessment, Climate Change, and Environmental, Social and Governance

(ESG) practices. She also contributes to executive and professional education through sustainability-related programmes at the Johannesburg Business School. Professor Modley has extensive postgraduate supervision experience, having supervised more than 20 completed Master's students and one Doctoral graduate, while currently supervising several Master's and PhD candidates. She has played a key role in curriculum development, programme review, academic quality assurance, and educational leadership, including serving as Deputy Head of Department from 2021 to 2025. Her teaching philosophy is grounded in experiential and applied learning, integrating fieldwork, community-engaged projects, sustainability initiatives, digital learning approaches, and interdisciplinary problem-solving into the classroom. Her professional background as an environmental consultant and sustainability specialist enriches her teaching and strengthens links between academic theory and industry practice. Her interests include teaching and learning enhancement, digital pedagogy, and student engagement.

## Moodley, Tevin

Dr Tevin Moodley is a Senior Lecturer in the Academy of Computer Science and Software Engineering at the University of Johannesburg, where he teaches across undergraduate and postgraduate programmes in Computer Science, Software Engineering, and Artificial Intelligence. He has several years' experience in higher education and is actively involved in curriculum development, student mentorship, and the integration of industry-relevant practices into computing education. His teaching focuses on bridging the gap between academic learning and professional practice through project-based learning, industry engagement, collaborative software development, and experiential learning initiatives. He coordinates and mentors final-year software engineering projects and is involved in initiatives that expose students to authentic industry challenges and professional networking opportunities. His teaching interests include Software Engineering, Computer Vision, Artificial Intelligence, Cybersecurity, and graduate employability. In addition to his teaching responsibilities, Tevin supervises

postgraduate research students and serves as Director of the Centre for Cyber Security. He is also Chair of the Faculty of Science Research Ethics Committee. His Scholarship of Teaching and Learning interests focus on work readiness, student engagement, authentic assessment, experiential learning, and the development of pedagogical approaches that prepare computing graduates for success in rapidly evolving professional environments.

## Moroeng, Ofentse

Dr Ofentse M. Moroeng is a Senior Lecturer in the Department of Geology at the University of Johannesburg, where he contributes to undergraduate and postgraduate teaching. He teaches first-, second-, and Honours-level courses and supervises Master's and Doctoral candidates, supporting the development of emerging geoscientists. His teaching philosophy is grounded in the principle of relatability, which he engages both in practice and scholarship. This approach emphasises connecting curriculum content, pedagogy, and learning environments to students' diverse identities, cultural contexts, and lived experiences. Drawing on this work, he adopts inclusive strategies that foster meaningful engagement while consciously avoiding the marginalisation or othering of students. Dr Moroeng is committed to cultivating a learning environment that is both academically rigorous and socially responsive. Through contextualised examples, reflective practice, and adaptive teaching methods, he aligns his pedagogy with the realities of students who may face systemic barriers to success. In doing so, he enhances students' understanding of complex concepts, while fostering a sense of belonging and intellectual agency, encouraging them to see themselves as active participants in scientific discourse.

## Mpekoa, Noluntu

Prof Noluntu Mpekoa is a distinguished academic whose career reflects over 18 years' dedicated lecturing and five years of industry experience. Her teaching spans a wide range of subjects, including Informatics, Information Security, Communication Networks, Advanced Communication Networks, and Network Security, delivered at undergraduate and postgraduate levels. Throughout her teaching career, Prof Mpekoa's philosophy has

evolved from emphasising her own teaching to centring student learning, and ultimately to a holistic recognition that teaching and learning are inseparable. She strives to balance five classroom dialectics: imparting knowledge while facilitating understanding; integrating theory with application; offering support while presenting challenges; maintaining rigour while encouraging creative experimentation; and respecting diverse student needs while ensuring fairness. Her excellence in teaching was recognised at the Central University of Technology (CUT), where she received the VC Staff Excellence Award in the category of Early Career Teaching. Prof Mpekoa was also part of the prestigious Teaching Advancement at University (TAU) Fellowship during 2015/2016. As a Research Professor at Unisa, she continues to pioneer innovative teaching practices while integrating her expertise in ICT with broader social impact. Her contributions to teaching and learning have shaped future leaders in technology and inspired a culture of excellence in higher education.

## Nkosi, Thulani

Mr Thulani Nkosi is a Lecturer in Genetics and Microbiology at the University of Johannesburg and is currently a PhD candidate in Bioinformatics and Computational Biology at Stellenbosch University. With several years' higher education teaching experience, he has taught undergraduate modules in Biochemistry, Microbiology, and Biotechnology, as well as mentored postgraduate research projects. His teaching practice spans laboratory instruction, curriculum development, and student mentorship, with a strong emphasis on fostering critical thinking and applied learning. He has coordinated student-led initiatives as the Chairperson through the Biotechnology and Food Technology Student Society and the South African Society of Bioinformatics Student Council, advocating for inclusive learning opportunities and professional development in bioinformatics. His teaching innovations include integrating digital learning tools into laboratory-based courses and promoting student engagement through collaborative projects. Thulani's interest in the Scholarship of Teaching and Learning (SoTL) is reflected in his commitment to equity in diagnostics education and iterative improvement of teaching practices. He views teaching

as a dynamic process shaped by both multidisciplinary expertise and student-centred approaches, aiming to prepare learners for impactful contributions in Science and Public Health.

## Nyabadza, Farai

Prof Farai Nyabadza is a Professor of Applied Mathematics and Head of Department in the Faculty of Science at the University of Johannesburg, South Africa. With over two decades' experience in higher education, he has taught a wide range of undergraduate and postgraduate courses, including Applied Calculus for the Social and Life Sciences and Mathematical Biology. He has developed and coordinated a number of academic programmes. Professor Nyabadza has supervised over 100 Honours and Master's students and 20 Doctoral candidates to completion during his career. His commitment to curriculum development is evident in his co-authored textbooks, *Introduction to Applied Calculus for Social and Life Sciences* (Juta Publishers), and his lecture notes in Mathematical Biology. He has a keen interest in making Mathematics accessible and relevant, which has informed his broader educational outreach and his engagement with the Scholarship of Teaching and Learning (SoTL).

## Pillay, Kriveshini

Prof Kriveshini Pillay is currently a Full Professor of Analytical and Environmental Chemistry in the Department of Chemical Sciences, University of Johannesburg and has 25 years' experience in teaching at a higher degree institution. Since joining the UJ, she has been involved in teaching miscellaneous first-year General Chemistry modules offered to both the Analytical Chemistry and Service Course students. She has also taught Inorganic Chemistry 2 and Analytical Chemistry 3 modules. She has, to date, hosted seven post-Doctoral research fellows, and graduated 22 MSc. students and 19 PhD students. She is currently supervising one post-Doctoral research fellow, 5 PhD and 2 MSc. students. She has been proactively involved in curriculum development and in developing learning materials for Chemistry modules offered by the Academic Development Centre. She has also served as a first-year module and academic performance co-ordinator, member of the Faculty Teaching and Learning Committee,

Deputy HOD: Teaching and Learning and member of Senex. Prof Pillay has been proactively involved in developing teaching and learning tools to facilitate the learning of Descriptive Chemistry. She has twice been nominated for the Vice-Chancellor's Teaching Excellence Awards. Her interests are in developing digital tools to facilitate the learning of Chemistry.

## Rampedi, Isaac

Prof Isaac T. Rampedi is an Associate Professor with a strong commitment to advancing the quality of teaching, research, and community engagement in the higher education sector in South Africa. He has taught Geography and Environmental Management for many years at undergraduate and postgraduate levels in several universities, including the University of Johannesburg. His academic work spans interdisciplinary and sustainability discourses in Environmental Management and integrates theory with professional practice. He has contributed immensely to curriculum development, postgraduate supervision, and collaborative research initiatives, mentoring students and early-career scholars towards academic and professional excellence. He has supervised more than 60 Master's degree students and 10 PhD students towards successful completion of their research projects. At the University of Johannesburg, he has been a key role player in the introduction and development of a brand-new postgraduate degree qualification, namely, a Bachelor's Honours (Environmental Management and Sustainability) degree programme. Beyond academia, he actively engages in knowledge exchanges and environmental problem resolution through conferences, symposia, and liaison roles with partners in the environmental management sector in South Africa and globally.

## Schoeman, Thea

Dr Thea Schoeman began her academic career in 1994 and has since built an extensive teaching, research, and supervision profile in Geography and Environmental Management. Over the course of her career, she has taught almost all undergraduate courses in these fields, demonstrating both breadth of expertise

and a deep commitment to student learning. She regards teaching as her true passion and has dedicated much of her academic work to creating meaningful, engaging, and applied learning experiences for students. Thea has supervised Honours, Master's, and Doctoral students across a wide range of research topics, contributing to the development of emerging scholars and professionals. Her research interests include waste management, with a particular focus on recycling, e-waste, waste minimisation, and sustainable environmental practices. Her passion for teaching has also extended beyond the university classroom through the development of short learning programmes designed to upgrade the knowledge and skills of Geography teachers. In addition, she has published in the Scholarship of Teaching and Learning, addressing topics such as mapwork, Geographic Information Systems, Sustainable Development Goals in education, and environmental education.

## Sebola, Tendani

Dr Tendani Edith Sebola is a Lecturer in the Department of Biotechnology and Food Technology in the Faculty of Science at the University of Johannesburg. Dr Sebola has over 6 years' teaching experience. She has taught Microbiology in different courses and disciplines such as Microbiology 3 for a Diploma in Biotechnology, Microbiology 2 for Diploma in Biotechnology and Diploma in Food Technology, Microbiology for Bachelor of Health Environmental, Medical Microbiology for Magister Technologiae in Homoeopathy and Magister Technologiae in Chiropractic and Microbiology 2A for Baccalaureus of Optometriae. She is a committee member for Departmental Teaching and Learning Committee and a Post Graduate Coordinator within the Department of Biotechnology and Food Technology. She is a Faculty Transformation Champion Committee Member within the Faculty of Science, and an Editorial Board member for the Faculty of Science book on the Scholarship of Teaching and Learning at the University of Johannesburg. Her interest in teaching and learning enhancement lies in creating engaging, student-centred educational experiences. She achieves this by using active interactive learning methods and supporting critical thinking and diverse learner needs. She treats the classroom as a laboratory, where she continuously evaluates,

and publicly shares evidence-based pedagogical practices that improve student learning outcomes.

## Ueckermann, Henriette

Dr Henriette Ueckermann is a Lecturer and Instrument Scientist in the Department of Geology at the University of Johannesburg. With a career spanning more than two decades across leading academic and research institutions worldwide, she combines expertise in innovative laboratory research, commercial scientific applications, and the training and mentorship of emerging Researchers. Her extensive experience provides students with a strong appreciation of both the scientific foundations and practical applications of geology. Dr Ueckermann currently teaches first-year Geology, where her educational approach focuses on bridging the gap between complex theoretical concepts and their real-world significance. Drawing on her broad scientific background, she introduces students to the fundamental principles of Geology while demonstrating their relevance to contemporary scientific, environmental, and industrial challenges. Recognising that effective teaching requires continual adaptation, she regularly develops and refines her teaching strategies in response to student engagement, performance, and feedback. Her educational philosophy is centred on creating an inclusive and dynamic learning environment that promotes curiosity, critical thinking, and a deeper understanding of the geosciences.

## Vorster, Clarisa

Dr Clarisa Vorster is a Senior Lecturer at the Department of Geology, UJ. She is an experienced educator and academic professional with a strong passion for teaching, and student development. In her 15 years' lecturing experience, she has contributed to the instruction and curriculum development of various modules, most notably sedimentology and basin analysis at both undergraduate and Honours levels. Her role as leader of Geology field-based modules (field schools) at first-year, second-year and Honours-level addresses her commitment to academic excellence, student-centred learning, and the development of critical thinking skills that prepare students for

the professional environment. She is dedicated to fostering a culture of enabling students to connect theoretical knowledge with practical applications. She remains committed to shaping knowledgeable, skilled, and socially responsible graduates who are equipped to contribute positively to their chosen profession.

## Wagner, Nikki

Prof Nikki (Nicola) Wagner is the Director of the DSTI-NRF Centre of Excellence in Integrated Mineral and Energy Resource Analysis (CIMERA) and Professor in the Geology Department at the University of Johannesburg (UJ), Johannesburg, South Africa. Nikki graduated from RHBNC, London, with a Geology-Zoology Honours degree, and completed her PhD in 1998 (Wits). Shortly thereafter, Dr Wagner worked for Sasol. In 2006, she joined the School of Chemical and Metallurgical Engineering, Wits, and in 2014 moved to UJ Department of Geology. Prof Wagner has been involved in academic teaching for 20 years, from first-year (primarily field school), to teaching large Engineering classes, supervising, teaching, fieldwork and facilitating at Honours level, and training and supervision of over 50 postgraduate students. She has been involved in several SoTL-related initiatives, currently focusing on field school experiential learning.

## Yessoufou, Kowiyou

Prof Kowiyou Yessoufou is a Full Professor of Botany and Director of the African Centre for DNA Barcoding at the University of Johannesburg, South Africa. He has over 13 years' university-level teaching experience, during which he has taught a wide range of Botany and Environmental Management modules at both undergraduate and postgraduate levels. To date, he has supervised and graduated 8 PhD candidates and 30 MSc students. He has also coordinated the MSc Environmental Management programme for several years and has been instrumental in developing and launching six short courses across the Departments of Geography, and Botany, University of Johannesburg.

# Foreword

Scientific discovery has long been a catalyst for societal progress. From addressing climate change and food security to advancing healthcare, digital technologies, and sustainable development, the sciences continue to shape our future. Yet scientific progress depends not only on the creation of new knowledge, but also on our ability to educate the next generation of scientists. For a Faculty of Science, therefore, excellence in research must be matched by excellence in teaching.

This volume reflects that commitment. It showcases the Scholarship of Teaching and Learning (SoTL) as a scholarly endeavour that places evidence, critical reflection, and continuous improvement at the heart of teaching practice. The contributors demonstrate that effective teaching is not static; it evolves through systematic enquiry, responsiveness to student needs, and a willingness to innovate in ways that enhance learning.

Although the chapters span diverse scientific disciplines, they are united by a common purpose: to improve student learning and success. They explore authentic and experiential learning, reflective teaching practice, innovative assessment, and the thoughtful integration of digital technologies, including artificial intelligence, virtual laboratories, computational tools, and immersive learning environments. Importantly, these innovations are presented not as ends in themselves, but as purposeful pedagogical approaches that deepen understanding, strengthen engagement, and prepare students for the demands of a rapidly evolving scientific landscape.

The collection is equally significant because it is firmly grounded in the South African higher education context. As universities strive to widen access while improving student success, the SoTL offers a powerful framework for designing learning experiences that are academically rigorous, inclusive, and responsive to the diverse needs of our students. The chapters in this volume demonstrate how scholarly teaching can bridge the gap between disciplinary expertise and meaningful student learning.

This book is more than a collection of innovative teaching practices. It reflects a Faculty of Science that values educational excellence alongside scientific discovery and recognises that the preparation of future scientists requires both disciplinary expertise and pedagogical scholarship. By making their teaching practices visible and subjecting them to scholarly enquiry, the contributors enrich not only their own disciplines but also the broader conversation on Science education.

I congratulate the editors and authors for this valuable contribution. I hope that this volume will inspire lecturers to continue questioning, reflecting on, and strengthening their teaching practices, ensuring that our graduates are equipped not only with scientific knowledge but also with the curiosity, critical thinking, and adaptability needed to address the challenges of an ever-changing world.

**Professor Annah Moteetee**
**Executive Dean: Faculty of Science**
**University of Johannesburg**

# Chapter 1

# An assessment of student satisfaction in the teaching and learning experienced in the Environmental Management Master's Coursework Programme at the University of Johannesburg, South Africa

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## Abstract

This chapter reports on the assessment of student satisfaction levels regarding the Master's degree programme in Environmental Management at the University of Johannesburg. The research aimed to investigate students' satisfaction in the manner in which the programme was organised and presented to them during their enrolment years. The research adopted a mixed-methods research design comprising a survey and focus group discussions (FGDs), thus collecting and analysing both quantitative and qualitative data. Results revealed higher proportions of students who were satisfied with the support received from the organisation and presentation of the teaching content, teaching

methods and supervision support, thus enhancing their overall learning experiences in the programme. More specifically, a greater proportion (50%-61%) of students expressed satisfaction with various aspects pertaining to teaching and learning in the Master's programme. However, some (5%-22%) students expressed some dissatisfaction with certain components of the same course and certain barriers and challenges that constrained their learning opportunities. The results from this study have several implications for teaching practice and pedagogy (i.e. theory and the rationale behind such practices) at the University of Johannesburg and the professional development of potential environmental managers who graduate from this programme. Consequently, primary issues in the enhancement and improvement of the existing curriculum have been highlighted for redress so that the programme can continue providing the environmental management sector with a competent and skilled workforce.

**Keywords:** barriers and challenges; environmental management; Master's programme; student satisfaction; teaching and learning

## 1. Introduction

Globally, there is a growing research focus on the evaluation and quality of Master's coursework degree programmes mainly around their purpose and how students experience their effectiveness in terms of teaching and learning (Walsh & Tucker, 2011; Hays & Sharp, 2018; Guleid, 2022). The overall purpose of Master's coursework degree programmes is to promote the acquisition of knowledge and skills to conduct not only research but to meet the needs of continuing education for professional work (Hamilton *et al.,* 2014). Thus, such programmes address the need for personal and professional development that is different from that of research-based Master's degree programmes (Thomas, 2018). Generally, their purpose is to satisfy professional requirements associated with employee upskilling, career development, and sometimes to address alignments with new government policies (Hays & Sharp, 2018). Therefore, they are offered as a viable academic pathway for the delivery and offering of continuing education for different professional goals

(Drennan & Clarke, 2009). To this end, various research studies have been undertaken to document students' experiences and assess their degree of satisfaction with their design and implementation. Given the growing competition amongst higher education institutions (HEIs) to recruit students, acquire funding for their operations, increase their international rankings and gain a competitive edge, there is a need to understand students' expectations and their satisfaction levels (Twum & Peprah, 2020; Htang, 2021).

The Master's Coursework Programme in Environmental Management (MCPEM) at the University of Johannesburg (UJ) was introduced more than 30 years ago and contributes towards the teaching and training of students who will provide key knowledge and expertise in the environmental management sector, and allied professions in South Africa, African countries, and abroad (UJ Faculty of Science Yearbook, 2024). The programme provides students with a skilful application of environmental dimensions, tools, and techniques in order to facilitate informed decision-making and expert judgement spanning a wide diversity of scientific disciplines (UJ Faculty of Science Yearbook, 2024). Similarly, the conceptualisation of Integrated Environmental Management (IEM) in this programme is regarded as an important theoretical perspective from which environmental management principles can be integrated into decision-making processes in South Africa. Apart from the theoretical modules, the programme also acquaints students with the principles of research practice to enable primary data collection and analysis and to develop their skills in scientific argumentation, writing, and communication. Therefore, students become involved in practical primary data collection and analysis while developing their skills in scientific writing and the exposition of conclusions emanating from their research (UJ Faculty of Science Yearbook, 2024).

Regardless of the many years in which the MCPEM has been offered at UJ and the routine student evaluations of existing modules, no empirical or reflective research on student satisfaction has been undertaken. The same shortcoming applies to similar programmes offered by some of the universities

in South Africa where there is limited literature on students' perceptions of the value of environmental management courses. Evaluating student learning through reflection on their experiences is deemed essential for achieving quality education (Whalen & Paez, 2021). Such investigations can contribute to the advancement of the scholarship of teaching and learning in several ways. By examining and reflecting on teaching methods, assessment practices, and the effectiveness of supervision, researchers can identify effective practices for enhancing student learning outcomes. This can also inform curriculum renewal, thus ensuring that students acquire relevant knowledge, skills, and competencies for environmental management. Therefore, in this chapter, student satisfaction levels regarding the MCPEM programme have been assessed to gain a better understanding of its impact on their overall learning experiences and effectiveness in the training of environmental managers in South Africa. This is important because if HEIs are to re-invigorate and transform their pedagogical approaches meaningfully, it is imperative for them to place students' learning needs in their teaching-learning discourses and strategies (Acevedo-Duque *et al.,* 2023). The first research objectives sought to characterise student satisfaction in teaching, learning and the supervision support that were provided to them. Secondly, the value and benefits of studying and completing this programme successfully are described. Thirdly, the research identified barriers and challenges experienced during enrolment years.

It is anticipated that the results in this chapter will shed light on what can be undertaken to improve teaching and learning quality in the offering of the MCPEM at UJ, especially in line with some of the institution's strategic objectives. For instance, Strategic Objective number two at UJ aims, amongst other goals, to offer professional and general formative programmes that have a multidisciplinary and interdisciplinary character (University of Johannesburg, 2023). Similarly, the results from this investigation are important for identifying theoretical and practical aspects that can be strengthened to advance training and professional development in the environmental management sector in South Africa. Achieving these goals will ensure that students who graduate from the MCPEM programme acquire cutting-edge skills

and competencies that are indispensable in tackling a myriad of global environmental problems such as the impacts of climate change or the negative socio-economic impacts that may result from poor environmental decision-making processes. In the next section, a brief literature review on the importance and role of student satisfaction is provided and thereafter the research methodology is explained before the results, conclusions and implications are discussed.

## 2. Literature Review and Theoretical Contexts

Three main aspects were reviewed in the existing literature to help to contextualise and develop a theoretical context for the current research: (1) purpose of professional Master's degree programmes and their sustainability contexts; (2) importance of student satisfaction levels in HEIs; and (3) research considerations in the South African contexts, thus helping to clarify the need for assessing student satisfaction levels and their implications for improved educational offerings.

### 2.1. Professional Degree Programmes in Environmental Management

The majority of Master's degree programmes in environmental management and related sustainability disciplines emphasise the need for problem-based learning (PBL) as well as gaining critical and system thinking skills required to address complex environmental problems in an interdisciplinary and multidisciplinary manner (Vincent *et al.*, 2013; Trencher *et al.*, 2018). The connection between PBL and sustainability competencies is intertwined, especially in the field of environmental management, where students and professionals are tackling complex and real-world sustainability challenges (Carrió & Bastida, 2023; Nguyen *et al.*, 2024). More particularly, PBL is indispensable in the teaching of environmental science concepts because it requires students to not only solve environmental problems but also work cooperatively and collaboratively to acquire higher cognitive skills and to take responsibility for their own learning processes (Woltering *et al.*, 2009). Such learning also bridges the disconnection between

theoretical knowledge acquisition and professional development. As maintained by Annan-Diab and Molinari (2017), "integrating disciplines facilitates problem-solving and the promotion of a better understanding of each part that comprises a problem and fosters solutions which blend concepts from different disciplines" (Annan-Diab & Molinari, 2017). Whereas "multidisciplinarity" derives from thinking in a parallel mode between different disciplines to achieve certain goals, "interdisciplinarity" requires an integrated way of thinking that transcends disciplinary boundaries. All these skills are very important in the understanding of the many ramifications of sustainable development problems which are regarded as some of the most pressing global challenges of the twenty-first century.

Another important competence is gaining a global transformation mind-set in keeping with sustainability thinking and the achievement of the United Nations' 2030 Sustainable Development Goals (SDGs) (Trencher *et al.,* 2018). Inevitably, across the globe, several HEIs are training students for professional practices that can enhance the implementation and achievement of SDGs (Daù *et al.,* 2023). In this context, learning for sustainability is inherently transformative, as students are encouraged to acquire new knowledge and attitudes that are conducive to behavioural changes in favour of sustainable development and long-term environmental stewardship. Furthermore, it is essential to recognise that transformative learning is premised on the critical-constructivist theory that states that our interpretations of the world are based on previous experiences and perspectives from our communities, culture, and social worlds (Boström *et al.,* 2018). According to the critical-constructivist theory, learning is a socially constructed and collaborative activity that requires group work, increased communication, contact and interaction amongst both students and their teachers. As a result, for student-centred learning to happen, it is essential to enable them to re-examine, interrogate, and revise their experiences and perspectives both critically and reflectively in order to gain a deeper understanding of how sustainability practices can be infused into the decision-making processes in various contexts (Boström *et al.,* 2018).

## 2.2. Understanding Student Satisfaction

Existing literature reveals that student satisfaction with graduate and postgraduate degree programmes is a multi-faceted concept and arises from various sources such as the quality of teaching, curriculum relevance, research development opportunities, and skills development (Alam *et al.,* 2013; O'Mahony, 2017; Jereb *et al.,* 2018). Students are satisfied when educational institutions fulfil and meet their goals and expectations (Appuhamilage & Torii, 2019; Chaudhary & Dey, 2021). The satisfaction of students regarding their teaching and learning experiences is important to both universities and students alike. High levels of student satisfaction are connected to the achievement of learning outcomes in HEIs (Wong & Chapman, 2023). Such experiences are beneficial to HEIs because they can reduce student drop-out rates, enhance student loyalty and word-of-mouth testimonials, while advancing future collaboration between such institutions and their former students (Asare-Nuamah, 2017). Furthermore, attaining higher student satisfaction levels is central to the organisational mission of universities, especially as they are competing with one another in attracting new and retaining existing students (Motefakker, 2016).

There are many key success factors in the determination of student satisfaction levels. These factors may entail the quality of facilities at the hosting institutions, organisational reputation, service quality, and career development and employability, amongst others (Weerasinghe & Fernando, 2018). Apart from these factors, student satisfaction may be regarded as an important variable to assess the quality of teaching and learning in the offering and teaching of degree programmes (Calvo *et al.,* 2010). Previous studies have indicated that levels of satisfaction tend to increase when students realise that their instructors are insightful, helpful, and generally display friendly attitudes (Voss *et al.,* 2007). Thus, satisfaction or dissatisfaction regarding specific academic programmes depend on the varied experiences of students when their expected outcomes are either achieved or not fulfilled (Wong & Chapman, 2023). In earlier research conducted amongst eleven European countries, it was found that student satisfaction levels were comparatively stable despite some discrepancies in the educational systems being evaluated

(Weerasinghe & Dedunu, 2017). In Sri Lanka, results derived from regression analyses revealed the significant influence brought by the quality of degree programmes on student satisfaction levels in public universities, while the quality of academic staff was found to be statistically insignificant (Weerasinghe & Fernando, 2018). By contrast, student satisfaction levels were found to be high at the Guru Gobind Singh Indraprastha University in India, as their staff and faculty were perceived to be knowledgeable and responsive to their requests and problems (Chaudhary & Dey, 2021). Furthermore, in an effort to assess the quality of instruction rendered to students at the University of Western Australia, the institution investigated its performance by utilising Students' Unit Reflective Feedback (SURF) metrics (Stewart *et al.,* 2018). They followed a distinct "before-after" approach, thus enabling them to compare such metrices prior and after the roll-out of enhanced teaching practices tailored to identify and overcome weaknesses in two undergraduate units. However, their SURF metrices did not increase markedly after the planned interventions probably because of the challenges of quantifying a rise in SURF scores for units which were already scoring highly in terms of the parameters involved (Stewart *et al.,* 2018). In the aforementioned studies, the rationale and motivation for studying student satisfaction have been briefly summarised, thus, demonstrating their importance to the quality of education offered by universities, and how they can increase the value of their degree programmes for improved learning experiences of students.

## 2.3. Postgraduate Student Satisfaction Levels in South Africa

The roles of universities in enhancing student learning experiences and satisfaction levels is an important priority area for all degree programmes in South Africa, including Master's coursework programmes because they contribute towards the capabilities of current and future professionals in various economic sectors. While there is a proliferation of research that investigated student satisfaction levels in other study fields, especially at undergraduate levels (Lion *et al.,* 2016; Ezeuduji *et al.,* 2017; Younes *et al.,* 2022), there is scant literature on student satisfaction regarding the effectiveness of teaching

and assessments in the post-graduate degree programmes in South African universities. In one of the rural-based public universities in South Africa, the majority of students expressed gross dissatisfaction with the quality of teaching and learning which they received, although an insignificant minority were highly satisfied, thus, identifying possible barriers towards increased student enrolment at this institution (Lion *et al.,* 2016). Another study conducted at Stellenbosch University assessed the usefulness of a blended learning approach according to student satisfaction levels (Botha, 2018). The results showed some of the factors that required attention before maximum student satisfaction can be achieved, notably the lack of adequate support for "at-risk" students and the challenges coming from unstandardised and user-unfriendly online platforms. Given the limited research regarding student satisfaction levels in South Africa, especially with respect to postgraduate programmes in environmental management, more research is needed if HEIs are to produce generally supportive and meaningful teaching and learning experiences for their students. Hence, the present research in this chapter addresses this research gap by assessing student teaching and learning experiences and satisfaction levels with special reference to the MCPEM at UJ in South Africa.

## 3. Research Methodology

### 3.1. Study Population

The study population comprised all contactable former UJ students who completed the MCPEM during the 2011 to 2024 period. The MCPEM has three compulsory modules (UJ Faculty of Science Yearbook, 2024:128-130). Respondents to our survey and focus group discussions (FGDs) were postgraduate students who have completed these modules successfully. The MCPEM is well-known in South Africa and attracts students not only nationally but also from other countries. Full-time students and part-time students register for the Theory Module 1 (ENM9X03) and 2 (ENM9X04) during the first and second semesters of the first study year. On the other hand, the Research Module 3 (ENM9X81 and ENM9X82) must, in both cases, be completed before the end of the study period (UJ Faculty of Science Yearbook, 2024:128).

The MCPEM is registered and accredited with the South African Qualifications Authority (SAQA) which is a statutory organisation responsible for the registration of qualifications in the National Qualification Framework. The qualification is recognised by the South African Council for Higher Education (CHE) which is responsible for, amongst other things, study programme accreditation, development of academic standards, and the monitoring of the national state of higher education. Both theoretical modules (namely, ENM9X03 and ENM9X04) are complementary to one another in terms of curriculum content and teaching methods (UJ Faculty of Science Yearbook, 2024:128-130). Module 1 seeks to increase the exposure of students to the Environmental Management discipline and emphasises environmental awareness and associated environmental perspectives, thus, enabling students to develop important insights about the biosphere and how it is structured and functions, as well as the importance of environmental studies that relate to Environmental Management. Module 2 orientates students to the basic discipline of Environmental Management. This module equips students with essential skills, tools, and techniques and the environmental perspectives required to facilitate successful and meaningful environmental management and to promote the concept of sustainability and the skilful application of a variety of tools and techniques in order to attain informed decision-making based on sound information and expert judgement spanning a wide variety of scientific disciplines. The two modules are taught from multidisciplinary and interdisciplinary perspectives and require other competencies such as critical thinking, a sustainability mindset, and problem-based learning, amongst others. However, Module 3 is research-based, and requires students to be familiar with the principles of research, the identification and demarcation of research problems, and skills to perform the different steps for generating, presenting and discussing research findings, ultimately generating valid conclusions and associated recommendations (UJ Faculty of Science Yearbook, 2024:128).

Formal lectures in the teaching of theoretical modules are preceded by an introductory meeting at the beginning of

the academic year where the course content, schedule of weekly lectures, and assessment plans are explained to all students. It is also compulsory for all lecturers to attend and introduce their research niche areas, especially regarding the allocation of supervisors who will guide students in the execution of their research projects that will culminate in the writing of a minor dissertation and a research manuscript that is to be submitted to accredited journals for possible publication.

## 3.2. Research Design

In order to address the research aim and objectives in the present study, a mixed-methods research design with both quantitative and qualitative aspects was adopted. Similar research approaches have been conducted previously in related studies to address the study objectives formulated for the current research (Woltering *et al.,* 2009; Yeh, 2022). The mixed-methods methodology entailed combining two distinct types of data sets instead of relying either on quantitative or qualitative data alone (Ivankova *et al.,* 2006; Cavallaro *et al.,* 2018; Levitt *et al.,* 2018). Furthermore, the approach was based on the explanatory sequential strategy whereby the quantitative phase of data collection and analysis occurred first and was followed secondly by the qualitative phase, thus, requiring a two-phase procedure in line with other studies (Jamieson *et al.,* 2021; Jung *et al.,* 2023). The quantitative data collected by means of an online survey were required for understanding the statistical proportions and patterns in the satisfaction of students in terms of the teaching, learning, and assessments that were conducted in the MCPEM, while qualitative data shed light on their personal experiences, opinions, and contextual insights. This means that both data types were concurrently presented and compared during the analysis phase. This "merging" process of data is considered to be one of the main advantages or strengths of the sequential explanatory design in that it gives a holistic and nuanced understanding of the research problem while enhancing the validity of the results (Jung *et al.,* 2023).

### 3.3. Data Collection Methods

Data collection methods entailed a questionnaire-administered survey and FGDs. An online digitally composed questionnaire was compiled by using a Google Form; a Web-based application developed by the Google company (Jaiswal, 2024). Such online administration of questionnaires not only saved time and other resources but was flexible in that study participants were given an opportunity to respond at their own time. The online platform also promoted access to study participants or respondents who were based in different locations, thus, reaching them wherever they were located. A digital link to the Google Form was sent to the email addresses of various study participants who had already indicated their willingness to participate in the research. Once the Google Form was sent to students, some of them were followed telephonically and by further emails in order to remind them about the need to complete the survey questionnaire. For this first phase of the research, a period of six weeks was allowed for participants to complete the questionnaire. Subsequently, the second phase of data collection was based on FGDs guided by semi-structured interviews conducted via the online platform enabled by Microsoft Teams. This means that study participants were allowed to join the discussions via the Teams application or Web browser. The time for such meetings was scheduled directly in Teams, Microsoft Outlook, or started instantly with the "Meet Now" option on Teams. Such meetings were held for about two hours per session.

Existing data at UJ based on previous student records for the MCPEM, email contacts, class lists and marks sheets for different years of enrolment constituted the study population for the research. On average, since the year 2011, about ten students were admitted to the current MCPEM annually, thus, totalling a study population of 130 former students for the 2011 to 2024 period. When the first round of emails was sent to 130 students, only 49 students responded and expressed their willingness to participate in the survey. Out of these 49 students, only 23 completed the online questionnaire, thus yielding a response rate of nearly 47%. While the number of responses (i.e. 23) from the first phase of data collection is not generalisable and representative of all students who completed the MCEPM in previous years, the

data set is deemed sufficient to reveal important insights and useful lessons about student satisfaction levels, especially as FGDs constituted the second phase of data collection.

## 3.4. Questionnaire Instrument

The questionnaire instrument used in the surveys had closed-ended questions and asked not only the demographical attributes of student participants but primary data on the different aspects of the degree programme that have a bearing on their satisfaction levels. As already mentioned, previous studies have indicated that overall student satisfaction levels at universities and similar institutions are influenced by various factors (Jereb *et al.*, 2018; Nortvig *et al.*, 2018:46). Consequently, the following criteria (Table 1.1) were derived from different literature sources that investigated student satisfaction levels from the perspective of the quality of university degree programmes. These criteria generally focused on, amongst other things (Table 1.1), the extent

**Table 1.1:** Some of the criteria for measuring student satisfaction.

| Criteria for measuring student satisfaction | Literature sources |
|---|---|
| Coursework and curriculum organisation | Browne *et al.*, (1998) |
| Teaching methods and quality of learning | Jereb *et al.*, (2018) |
| How assessments are conducted and feedback given | O'Mahony (2017) |
| How supportive is the learning environment | Jereb *et al.*, (2018) |
| Theoretical and professional knowledge acquisition | Arruzza and Chau (2021) |
| Gaining critical skills, competencies, and employability | Bordean and Sonea (2018) |
| Supervisory guidance and support for research | Alam *et al.*, (2013) |

of coursework and curriculum organisation, effectiveness in teaching, and student learning experiences, support for research supervision, planning and execution of assessments as well as knowledge and skills acquisition. In addition to these criteria, some of the questions were based on the challenges and barriers that students experienced while they were studying for the MCPEM at UJ. Knowing the extent of the challenges and barriers experienced by students is important, as it can shed light on their magnitude and how institutions can resolve them for improved student experiences (Smith *et al.,* 2020).

## 3.5. Focus Group Discussions

After the collection of quantitative data, the second phase of data collection was undertaken by means of FGDs whose detail is explained in the following sections.

### *3.5.1. First phase of data collection, data analysis and interpretation*

The questionnaire instrument was designed to obtain primary data in order to address the research aim and objectives. Questions that were asked to study participants required simple "Yes" or "No" responses and multiple-choice answers. However, to gain a better understanding of student satisfaction levels, some of the questions were formulated in the form of various statements (or items) that were arranged in a five-point Likert scale. As indicated in previous studies (Joshi *et al.,* 2015; Batterton & Hale, 2017), the statements or items must be formulated in a way that reveal specific dispositions, opinions or attitudes of study participants towards the issues under investigation. In the present research, student participants responded to the statements by various options on the questionnaire ranging from "strongly agreeing" (1) to "strongly disagreeing" (5) with them. Furthermore, the instrument comprised four main sections based on the following aspects:

- Section A (Biographical and demographical aspects)
- Section B (Teaching, learning, research supervision, and assessments)
- Section C (Value that students derived from the programme)
- Section D (Barriers and challenges experienced)

Whereas Section A was based on the biographical and demographical attributes of student participants, questions formulated in Section B sought to gauge student satisfaction levels in terms of how they experienced overall teaching and learning regarding the organisation and effectiveness of lectures, learning materials and methods, execution of assessments, and the research supervision support which they received towards their individual research projects. Questions asked in Section C assessed the value and benefits that students derived from their studies and completing them successfully, for example, employability, knowledge and skills acquisition, professional registration, and the ability to enrol for further studies. In Section D, students were given an opportunity to indicate some of the barriers and challenges which they experienced during and after the completion of their study programme.

3.5.1.1. Reliability and validity test

In terms of ensuring the validity and reliability of the questionnaire, Cronbach's Alpha coefficients were calculated for specific sections of the instrument (Table 1.2). The following results were obtained for key sections of the instrument and they ranged from a value of 0.74 (satisfaction with research supervision) to 0.93 (barriers and challenges that students experienced). The results indicate that the various items measuring each variable are acceptable and demonstrated comparatively high internal consistency for the present research.

**Table 1.2:** Cronbach's Alpha for key sections of the questionnaire.

| **Variables** | **Cronbach's Alpha** |
|---|---|
| Satisfaction with teaching and learning | 0.78 |
| Satisfaction with research supervision | 0.74 |
| Value and benefits derived from programme | 0.81 |
| Barriers and challenges that students experienced | 0.93 |

Lastly, the analyses of the primary data gathered from questionnaires was performed by calculating the percentages of student participants and the results were expressed in the form of tables, pie charts, and bar charts.

#### 3.5.1.2. Ethical considerations

The collection and analyses of all primary data gathered in this study was guided by institutional considerations and safeguards at the University of Johannesburg. The research project was approved by the UJ Faculty of Science Research Ethics Committee with associated protocol references (2023-05-03/Rampedi). At all times, the respondents were duly informed about the study goals and their right to participate or not without incurring any adverse impacts on their well-being and welfare. Moreover, the principle of prior informed consent was strictly adhered to; meaning that only respondents who offered their willingness or consent to participate were considered further for the purpose of obtaining data from questionnaire-administered surveys and FGDs. Respondents were also free to exit data collection processes at any time and all data collected were anonymised and coded, thus protecting their privacy and confidentiality.

### *3.5.2. Second phase of data collection, analysis and interpretation*

FGDs were held with a relatively fewer number (sixteen students) of students who were willing to share their personal opinions, ideas, and experiences and some of the benefits which they derived from enrolling and registering for the MCPEM. Focus group interviews (FGIs) with students were held in groups of five to six students per session and the discussions took place via MS Teams. Each session lasted for about two hours. For each session there were two to three facilitators who collaborated with one another in asking open-ended questions to study participants. Participants were then given an opportunity to elaborate on their experiences in terms of the teaching, learning, and assessments that took place during the MCPEM, including the quality of the support which they received from research supervisors. Comments made by participants were recorded by the facilitators

and were later summarised for qualitative data analysis. Data analysis was undertaken by means of content analysis.

### 3.6. Study Limitations

The study was constrained by few limitations. Not all students responded to our online survey and FGDs that followed the first and second phase of data collection, respectively. The quantitative results were generated from the responses received from only 23 students, which represented about 47% out of the 49 students who were randomly selected to participate in the surveys. While the number of sampled students is relatively limited to adequately represent all students who completed the MCPEM at UJ during the 2011 to 2024 period and the data are not suitable for complex statistical tests like regressions, we consider it sufficient for descriptive statistics in the form of means, percentages and standard deviations. Similarly, qualitative data were obtained from sixteen respondents. Secondly, the research undertaken is based on student experiences of the MCPEM course at the time of their enrolment for the programme. Thus, the results generated are not able to show how student satisfaction varies over time. However, the results generated contribute original findings which shed light and provide implications on how the MCPEM can be improved for effective delivery in its teaching and learning components at the University of Johannesburg.

## 4. Results

### 4.1. Demographical Aspects of Respondents

In total, 23 former students in our MCPEM degree programme responded to the online questionnaire. Male respondents amounted to nearly 40% (i.e. 38.1%) and female respondents accounted for 61.9% of the total sample (Figure 1.1). Regarding their ages (Figure 1.2) at the time of survey, the majority (66.7%) of them were in the 30 to 39 years category while only 3.8% were in the 20 to 29 years class, respectively. However, other age categories such as 40 to 49 year-olds were less represented (9.5%).

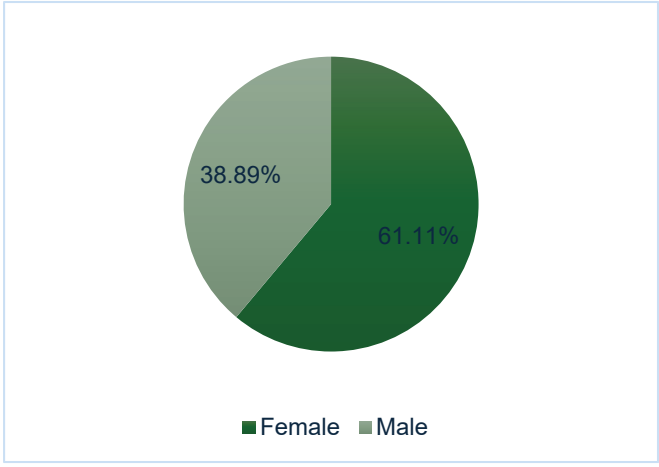



**Figure 1.1:** Gender of respondents

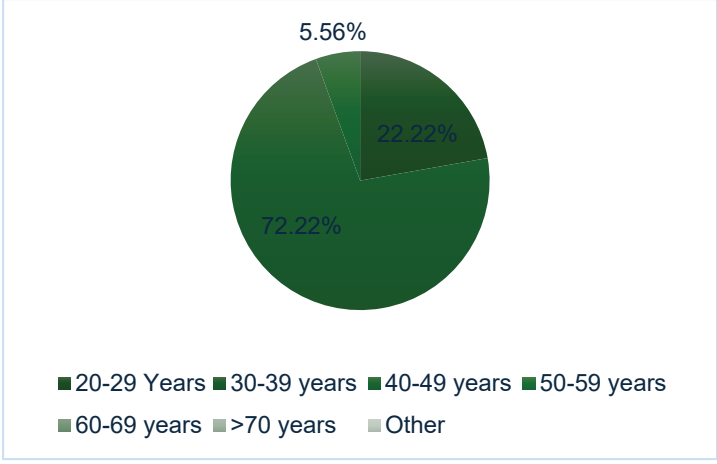



**Figure 1.2:** Age groups of respondents.

Whereas a large proportion (77.78%) of respondents were in full-time employment during their study period, a lower proportion of them were either self-employed (11,11%) or unemployed (5.56%) (Figure 1.3).

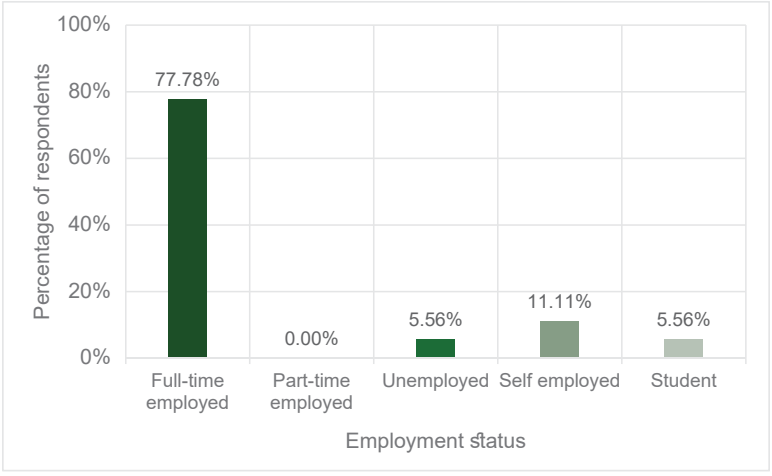



**Figure 1.3:** Employment characteristics of respondents.

Out of all respondents who had completed their degree programme successfully, only 5.56% of them furthered their education to obtain a PhD qualification (Figure 1.4). This means that their Master's degree qualification served as a stepping stone for PhD degree enrolment in subsequent years.

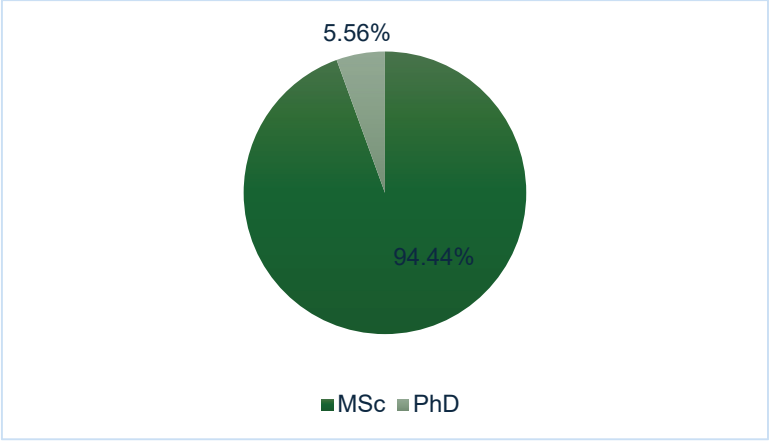



**Figure 1.4:** Educational qualifications of respondents.

The proportion of respondents who completed their studies in record time was 61.9% compared to those (38%) who exceeded the allocated study period (Figure 1.5). Completing studies in record time means two years for full-time students and three years for part-time students.

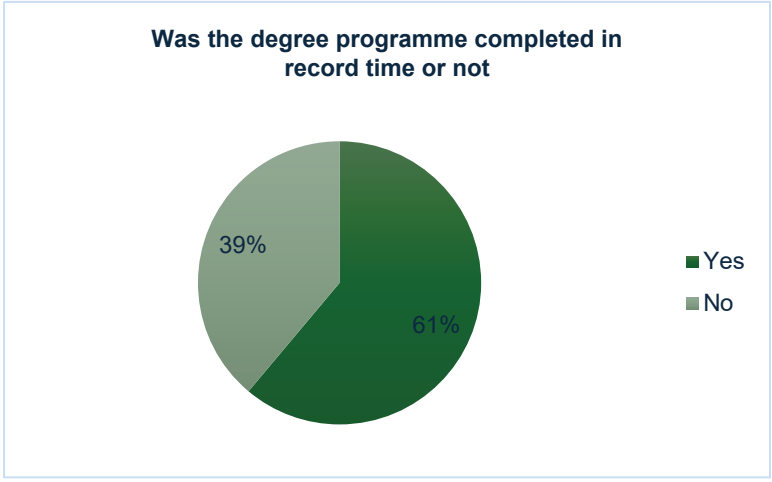



**Figure 1.5:** Completion time of studies.

## 4.2. Satisfaction with the Organisation and Delivery of Teaching and Learning

As shown in Figure 1.6, most respondents (90.5%) claimed to have attended the compulsory introductory meeting that is traditionally held before the commencement of lectures in any academic year. During such a meeting, a detailed overview of course information is provided, including module content, different types of assessments, and potential supervisors for guidance on the research projects and the writing of dissertations (Figure 1.6). Over 95% of respondents who attended introductory meetings mentioned that such communications were very helpful in creating awareness about what is expected from them for completing the degree programme successfully.

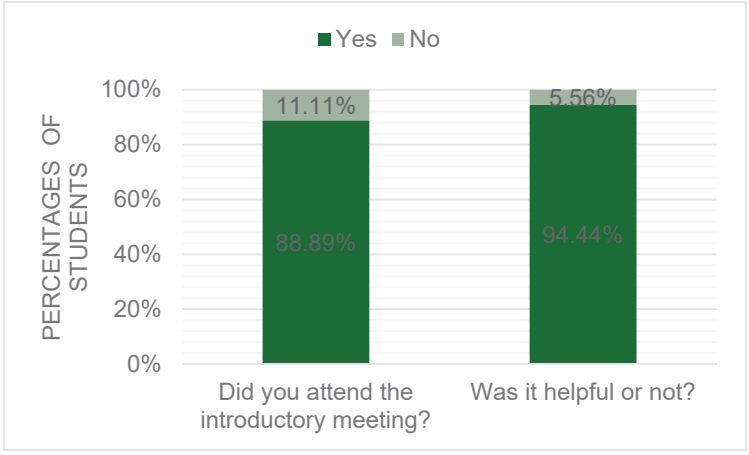



**Figure 1.6:** Proportions of respondents who attended the first introductory meeting prior to beginning of academic programme.

Satisfaction regarding the teaching and learning support given to students is summarised in Figure 1.7. Amongst all statements representing support efforts towards students, 50% to 61% of respondents expressed positive experiences regarding their experiences pertaining to teaching and learning in the programme.

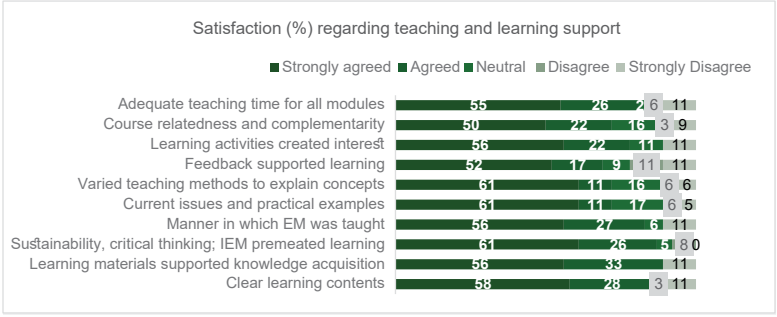



**Figure 1.7:** Proportions of respondents on their satisfaction regarding teaching and learning support.

More specifically, making the learning outcomes more clearer to students (58%; M=4.33; SD=1.197), teaching the concept of sustainability in a better light, encouraging critical thinking and an understanding of the concept of integrated environmental management (IEM) (61%; M=4.19; SD=1.209), and rendering the learning content relevant to the professional world by bringing out current issues and practical examples (61%; M=4.14; SD=1.195) were all strongly agreed to by a higher proportion of respondents. Other aspects that were agreed to by most respondents included the variation of teaching methods to explain certain concepts during lectures (27%; M=4.19; SD=1.167) as well as developing interest in studying the learning content and knowing more about the environmental management sector in South Africa (22%; M=4.19; SD=1.195).

Some of the positive experiences expressed in Figure 1.7 are in alignment with viewpoints mentioned by various respondents during FGDs. For instance, direct remarks made by two respondents (R1, R7) were invariably positive:

> "The teaching and learning attained in the Master's degree programme in environmental management was a very good experience for us, as it was relevant to our learning needs. I was exposed to different aspects of the environment and attempts to manage human impacts sustainably. We received a lot of knowledge on several topics such as environmental pollution, water quality management, air quality management, biodiversity issues, environmental reporting, environmental assessments as well as related legal and regulatory matters. Thus, the scope of the modules was broad, and this enriched our knowledge of diminishing natural resources in certain areas, problems of changing climates, and sustainability considerations". [R1]

> "So much interesting content was taught in this programme, as I have completed my undergraduate degree programmes in other study fields and not environmental management. More specifically, I came into this programme from a background of agricultural management and extension in my junior degree. Thus, before enrolling in the Master's

> coursework programme, I did not have a technical and scientific grasp of environmental science, local and global environmental issues, as well as dealing with sustainability challenges that threaten our biosphere. Therefore, this programme opened my eyes and perspectives about the need for sound environmental governance that is informed by a deeper understanding of the different parts of the environment, their limits of acceptable change, and just how important is good environmental management to maintain environmental quality". [R7]

From the aforementioned remarks, respondents not only acknowledged the appropriacy and relevance of the lecture contents in this programme but also the particular didactical approach that was applied during teaching. All students were taught various topics such as environmental pollution and the disruption of ecological processes, their relationships with economic, social, political, and regulatory factors, the concept of integrated environmental management, the importance of sustainable development as well as the tools and skills that are needed to achieve this end goal.

While the proportions of students who strongly agreed with the various statements that were relatively high on a Likert scale (Figure 1.7), it is important to indicate that some (6% to 11%) respondents expressed some disagreements. Such negative results are important because they highlight areas that require more teaching and learning support in this degree programme. For example, one respondent (R13) expressed the following opinion during FGDs.

> "Much as the content of the Master's course touched on the different aspects of environmental management, the scope and time devoted to the teaching of the vexing issue of waste mismanagement in South Africa and recycling challenges was very limited. These issues are very important from a sustainability viewpoint. Moreover, in some of the large metropolitan areas in South Africa, municipalities face several challenges in providing adequate waste management services. Another problem is

> that existing landfill sites have very few years remaining before they lose their airspace for waste disposal while there is no new available land commissioned for the construction of new landfill areas. That the issue of waste management is of national concern and many students in this programme are choosing waste management and recycling as topics for their research projects". [R13].

Furthermore, respondents were presented with several statements that represented their experiences on the quality of the supervision support received. The results are depicted in Figure 1.8. Some of the statements were strongly agreed to by most respondents and their mean values ranged from 4.10 to 4.30; thus indicating a higher level of consistency amongst respondents. More particularly, greater proportions of students strongly agreed with statements that depicted effective allocation of research supervisors (72%; M=4.25; SD=1.33); provision of adequate guidelines for conducting literature reviews (72%; M=4.30; SD=1.174); and precautionary measures being undertaken to prevent plagiarism (61%; M=4.30; SD=1.196).

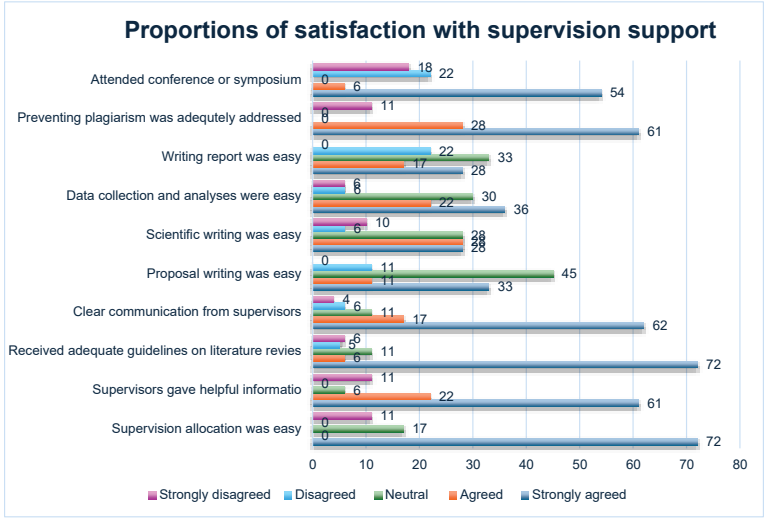



**Figure 1.8:** Proportions of student satisfaction regarding the supervision support received.

In line with the results on the research supervision support received by students, some of the support that students expressed from FGDs were summarised by various respondents as follows (R1; R8; R11):

> "My supervisor supported my research project throughout its different phases. I also received relevant information for further career development beyond the formal association we had during the supervision period". [R1]
>
> "My supervisor was very good even through my initial research abilities were not up to standard. Thus, in the end, I managed to complete my research dissertation successfully". [R8]
>
> "Despite my supervisor having a tight work schedule and guiding many students in their research activities, he always made an effort to give constructive feedback timeously and in a friendly manner". [R11]

While the majority of statements regarding research supervision seemed to be positively rated by most respondents, some experiences were assessed in a rather negative light, thus indicating certain areas of discontent. For example, a relatively lower percentage (33%; M=3.8; SD=1.056) of students strongly agreed with the statement that the writing of research proposals was easy. This means that even if some (i.e 33%) students were in agreement that proposal writing was easy, their positive responses in this instance were not enormous, thus symptomatic of underlying challenges.

In addition to these quantitative results, other research supervision problems were expressed more succinctly by the analyses of the relevant qualitative data. One of the respondents (R13), during FGDs, highlighted another difficulty and how it was resolved in the following manner:

> "I experienced some problems in the manner in which my research project was supervised in the host academic department. Two supervisors were involved. The first supervisor was external to the department and had to be discontinued as there was a lack of progress. Consequently,

> I always received very delayed feedback and my research work fell behind. This affected the drafting and writing of my research proposal badly. However, things improved markedly when I was allocated the second supervisor. With guidance received from the second supervisor, I completed both my research proposal as well as the drafting and submission of my research dissertation for final examinations in one year". [R13]

## 4.3. The Value of the Programme to Students

As far as the academic and professional value that the MCPEM has generated for the students, relevant experiences are summarised in Figure 1.9. Whereas most statements on the programme value were strongly agreed to by most students, some of them were not widely accepted. Nearly 70% (67%; M=4.24; SD=1.261) of respondents valued the extent to which the programme provided them with practical knowledge about the environmental management sector in South Africa. In descending order, the ability to apply successfully for professional registration was viewed in a stronger light by 61% (M=4.00; SD=1.225) of respondents. However, other benefits were not rated highly amongst certain respondents and these entailed the degree to which the qualification enabled them to find employment either in the environmental management sector (28%; M=3.43; 1.287) or a different sector (28%; M=3.10; SD=1.447).

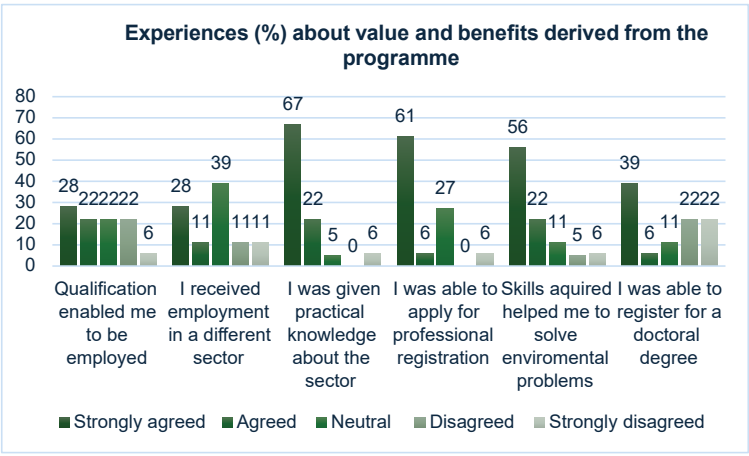



**Figure 1.9:** Value and benefits derived from the programme.

A high degree of congruence was found between the patterns seen in the quantitative data (Figure 1.9), and the verbal and textual narratives that the respondents provided when they were asked about the value of the MCPEM. Various respondents expressed their satisfaction about the value that they derived from the MCPEM in the following narratives:

> "Completing this programme was a great achievement for me as I was able to find a job in the environmental consulting sector that required knowledge of environmental impact assessments, environmental monitoring, and auditing, along with the designing and implementation of environmental management systems. At my workplace, I deal with these tools daily, thus helping me to become relevant and productive at my job". [R3]
>
> "I liked the idea whereby some guest lecturers were appointed to teach in this programme. Some of them were technical experts in their respective occupational fields, thus insightful in broadening our understanding of the more practical and industry-related issues in the various aspects of environmental management. In other words, teaching came from internal and external experts, thereby enriching our learning experiences and preparing us for jobs in the environmental sector and allied professional fields". [R5]
>
> "I found the teaching of concepts such as the different methods and techniques of conducting sustainability reporting very helpful as this is directly relevant to the work that I am currently doing at my workplace". [R12]
>
> "We were equipped with a sound theoretical and practical knowledge of the tools, skills, and competencies needed for proper environmental decision-making and prioritising the management and reduction of all types of environmental impacts". [R14]
>
> "The writing of research proposals during my studies has provided me with an opportunity to gain competencies that I practice at my workplace on a routine basis. At my workplace, I am required to write new proposals from time to time to acquire funding for the environmental work that we do". [R15]

## 4.4. Students Experiences Regarding Barriers and Challenges

Results on the barriers and challenges experienced by respondents during their studies are indicated in Figure 1.10. Whereas the proportions of respondents who agreed or strongly agreed with various statements that represented difficulties were in lower proportions, the percentages of respondents who expressed a high level of disagreement with them were relatively high. The results show that although such difficulties existed, only a few respondents had experienced them in a very significant manner. For instance, enrolling and studying for the programme whilst in full-time employment was experienced as challenging to some of the affected students. In fact, nearly 17%-30% (M=3.05; SD=1.284) of respondents faced this problem. By contrast, the majority of respondents disagreed with most statements that denoted the barriers which they experienced whilst studying for the MCPEM. Over 70% (72%, M=2.19; SD=1.123) of respondents strongly agreed that submitting assignments and other assessment reports did not pose any significant barriers to them.

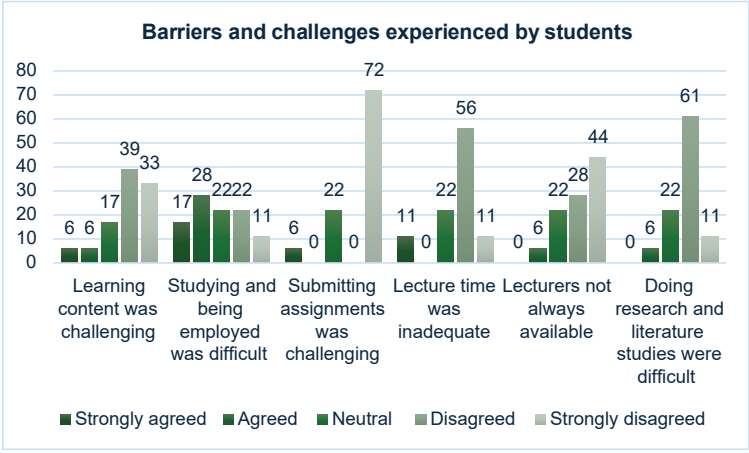



**Figure 1.10:** Barriers and challenges experienced by students.

Although the quantitative data indicated that only a minority of respondents encountered major challenges in the MCPEM (Figure 1.10), the qualitative insights from FGDs highlighted a

broader spectrum of difficulties experienced by students. Some of these challenges are summarised as follows:

> "While research supervisors were giving us the opportunity to complete our research reports adequately, it seems there was some mismatch in the manner in which some of the external examiners were assessing our work once our dissertations were sent out for final examinations. This is because the feedback reports I received for my minor dissertation differed markedly, and this confused me as to what was required of us". [R1]
>
> "It was extremely difficult juggling time between formal degree studies with my tight workplace schedule. What worsened my personal challenges was the 400 km journey that I undertook once or twice every week just to attend my lectures and to consult with my supervisor on the pace of my research and the guidance that I needed". [R2]
>
> "Despite the broad scope of the curriculum developed for this programme, I think the content must move with the times and, therefore, new topics such as environmental, social, and governance (ESG) issues, climate finance, climate justice, and environmental management for the circular economy must be given more coverage in the study materials so that the course remains relevant to developments in the field and new research directions". [R3]

## 5. Discussion of Results and Study Implications

The purpose of the present research was to assess student satisfaction about their experiences and the support which they received in terms of teaching and learning in the MCPEM. In addition, the value derived from the programme as well as the barriers and challenges experienced were analysed.

The demographical data indicated that the programme has attracted more (61%) female than male students. In fact, in any academic year during the last 10 to 15 years of this programme, the number of female students who enrolled has always exceeded the number of male students. Such a proportion of students is

in line with the institutional profile of 54% for female students (Gihring, 2022), although in the MCPEM it was relatively higher (61%). This finding highlights some of the significant progress in achieving gender equity and access to higher education in South Africa. Greater female participation in the MCPEM may strengthen the national research and innovation ecosystems, thus, bringing diverse perspectives to sustainability challenges and expanding the leadership pipeline of women in science, policy, and practice (National Planning Commission, 2012).

Nearly 77% of the former students were in full-time employment during their enrolment period, thus demonstrating the important role that the MCPEM has played in their career and professional development. Furthermore, about 60% of students completed their studies in record time. However, because 40% of students did not complete their studies in record time, this is suggestive of some of the existing challenges in the offering and management of this programme. Existing literature shows that the completion rates of Master's and Doctoral degree programmes in South Africa is an area of great concern because of high drop-out rates (Roets & Botma, 2012; Mphekgwana *et al.*, 2020; Cilliers *et al.*, 2023). Therefore, there is a need for interventions that can contribute towards overcoming existing barriers and challenges that students are facing during their enrolment years (Styger *et al.*, 2015; Massyn, 2018).

## 5.1. Satisfaction With Teaching and Learning

As alluded to earlier, the first research objective was to characterise student experiences and their satisfaction in terms of the manner in which teaching and learning were carried out in the MCPEM. The analysis of these results is instrumental in determining whether the teaching strategy in the MCPEM matches the students' cognitive and professional needs. Over 90% of respondents indicated that attending the first introductory or orientation meeting prior to the commencement of lectures was beneficial to them. The attendance gave them an opportunity to receive key information on the structure of the course, content of each module, lecturers responsible for each study unit, timetable of lectures, and which supervisors were available for guiding them in their individual research projects. Moreover, the introductory

meetings afforded them not only the time to meet with lecturers but also with fellow students enrolled for the same programme. Students were further afforded an opportunity to raise any teaching and learning problems that they may experience during the academic year to their individual lecturers, course coordinators as well as research supervisors. In this manner, the meetings inculcated a sense of belonging and fitting with other students and the learning environment as a whole; a point also highlighted by McKenzie *et al.,* (2024) in their study of the value of induction meetings for part-time distance learning students at the Open University in Wales. Similarly, the findings from the current research corresponds with documented empirical evidence that students can benefit from induction meetings prior to the commencement of the teaching and learning period during the academic year (Mathieson *et al.,* 2024:322).

To better understand how students were satisfied with the support and guidance that they received in terms of teaching and learning, both quantitative and qualitative data sets were analysed. To a large extent, there were marked convergences in what the results show, despite one area of divergence that was revealed by the analyses of qualitative data. Out of the ten different statements that expressed satisfaction levels or positive experiences with teaching and learning in the Master's programme, all of them were agreed (28%-33%) and strongly agreed (50%-61%) to by relatively higher proportions of respondents. Moreover, some of the means calculated for specific responses were comparatively higher as they ranged from 4.19 to 4.33, thus indicating greater levels of agreement and positive experiences amongst students. For example, nearly 60% (M=4.24; SD=1.179) of respondents strongly agreed with the statement that the learning materials in the MCPEM supported knowledge acquisition. The materials included in the various modules entailed not only study guides and a schedule of weekly lectures, but details of specific textbooks, published literature and other information resources from which students could access key information and knowledge. Previous researches show that sharing information about course content, learning outcomes, teaching and learning materials, and offering students access to the learning resources have a marked positive effect on students'

satisfaction levels (Calvo *et al.,* 2010; Yusoff *et al.,* 2015:87-93; Weerasinghe & Fernando, 2018).

While both quantitative and qualitative results point towards a greater frequency of satisfaction levels regarding teaching and learning activities, some respondents expressed some divergence and dissatisfaction, thus revealing some weaknesses in the teaching and learning components of the programme. This was particularly evident when it came to the extent to which respondents received timeous feedback from lecturers as the relevant statement was rated lower (52%; M=3.90; SD=1.300) than other more favourable responses. Thus, respondents were almost equally (i.e. 52%) split in terms of negative and positive experiences regarding timeous feedback for their assessment tasks. Furthermore, student dissatisfaction applied to the limited coverage of certain important topics in the existing course content, notably the limited teaching of (1) solid waste management; (2) environmental, social, and governance (ESG) issues and the importance of learning (3) climate finance. Many studies in South Africa (Godfrey & Oelofse, 2017; Mlotshwa *et al.,* 2022) have highlighted the challenges posed by increasing general and hazardous waste generation rates and the limited capacity of South African landfills to absorb waste, thereby highlighting the need to enhance both professional and practical capabilities in the waste management sector. Similarly, gaining knowledge about climate finance is important to the environmental management students because of the increasing role that such knowledge will play towards climate impact mitigation in the sub-Saharan African (SSA) region, including South Africa. Research shows that a just transition to a carbon-neutral economy in the SSA region needs transition finance for effective climate action (Winkler *et al.,* 2020).

Closely linked to student satisfaction with respect to teaching and learning, is how students experienced the quality of research supervision. Both sets of results revealed that the majority of respondents were relatively satisfied with the manner in which their individual research projects were supervised. Highly rated statements are denoted by higher means (M=4.10-M=4.30) and lower standard deviations (SD=1.119-SD=1.174).

Effective supervision allows students to develop their academic and scientific writing skills and communicate their findings in a meaningful and coherent manner (Drennan & Clarke, 2009). However, in this study it has been found that some students were dissatisfied with the MCPEM because of delayed feedback received from some of their research supervisors. As revealed by previous studies, when feedback to students is withheld, it delays the revision of their dissertations, slows down the attainment of research milestones, and increases the risk of students not completing their degree programmes within the expected timeframe (Amani *et al.,* 2022; Bahtilla, 2024; Amponsah *et al.,* 2025). In practical terms, this can mean extended study periods, higher costs, and postponed career opportunities (Chugh *et al.,* 2022). In light of these challenges, there is a need for improved and effective supervision of postgraduate students in the MCPEM, as this can contribute towards the advancement of some of UJ's 2035 strategic objectives (University of Johannesburg, 2026). Timely provision of feedback to students will enable them to complete their research projects within the stipulated study periods and to acquire research capabilities that can drive South Africa's transition to a green economy.

## 5.2. Satisfaction With the Value of MCPEM

The second objective in the research was to explore the value that students derived from enrolling and completing the MCPEM successfully. Understanding how students valued the programme is important because their enrolments, as in other countries, are driven by different needs such as academic development and ability to conduct research, gaining knowledge relevant for both professional practice and registration with accredited professional bodies, and accessing employment opportunities (Drennan & Clarke, 2009; Fischer & Jha-Thakur, 2013). More particularly, the MCPEM was designed to impart various types of skills such as critical thinking, sustainability thinking, problem-solving skills, and competencies needed for academic and professional development to the students. In keeping with UJ's Strategic Objectives for the year 2035, some of these skills are expected to prepare students to become resilient and think critically to

generate positive societal impacts and sustainability in the world (University of Johannesburg, 2026).

Amongst the six statements formulated to express student's satisfaction in terms of realising the value or benefits of the MCPEM, respondents who were in agreement or in strong agreement with them were in the majority despite the limited extent of those who expressed dissatisfaction. More strikingly, acquiring essential and key knowledge for the environmental management sector (67%; M=4.24; SD=1.261) and being able to register professionally as an environmental scientist or environmental assessment practitioner (61%; M=4.00; SD=1.225), were strongly agreed to by most respondents, thus highlighting positive experiences or high degrees of satisfaction with the MCPEM. The findings from such quantitative data were consistent with most themes that emanated from the qualitative narratives provided by respondents. For instance, some of the narratives by respondents expressed benefits such as the following ones:

- Imparting theoretical and practical knowledge,
- Enabling them to write scientific reports,
- Improving their proficiency in the use of various environmental management tools, and
- Gaining access to employment opportunities.

Similarly, other studies that estimated the value that students attached to or derived from other postgraduate study programmes entailed the potential for professional registration (Carrivick, 2011), realising increased career opportunities and employability (Jagganath, 2023; O'Callaghan *et al.,* 2024) and gaining the capacity for critical thinking and innovation (Jagganath, 2023). The benefits derived from the MCPEM in the present research may also be seen in terms of some of the requirements for the professional registration of environmental assessors in South Africa. For example, the Environmental Assessment Practitioners Association of South Africa (EAPASA) has listed several competencies for the professional registration of qualifying graduates in the environmental assessment sector (EAPASA, 2024). Such competencies include, amongst others, the capability to think critically and systematically, communication skills, problem-solving skills, maintaining professional conduct, and the ability to conduct applied research (EAPASA, 2024).

## 5.3. Barriers and Challenges

In terms of the different barriers that students experienced during their studies in the MCPEM, all six statements that expressed difficulties were to a large extent disagreed (28%-61%) to strongly disagreed (11%-72%) to by respondents. Moreover, given the mean values (2.14-3.05) of these statements on a Likert scale, there is mild disagreement (few barriers) to slight agreement (some barriers), thus, suggesting that while barriers were acknowledged, they were not generally experienced or perceived as severe or extremely overwhelming to most students. For example, the majority of students (72%) strongly agreed that submitting assignments was not a significant barrier. This means that administrative or procedural challenges (such as meeting assignment due dates, submission systems, and attaining workload balance) were not regarded as major obstacles to the respondents. However, some respondents experienced the balancing of full-time studies with workplace demands in a very negative light. Similarly, the interpretation of qualitative data on the barriers that students experienced revealed more areas of dissatisfaction. For instance, one respondent explained that some of her personal experiences and frustrations emanated from marked discrepancies in the outcomes received from external examiners regarding her minor dissertation. Similarly, this finding was regarded as one of the most important determinants of student satisfaction amongst postgraduate students enrolled in the School of the Built Environment in one university located in the north-west of England (Poon, 2019). According to existing literature, discrepancies in the external assessment of dissertations are sometimes inevitable and arise because of:

- Inadequate explanation of assessment guidelines and criteria to the examiners (Varshney, 2021)
- Applying and interpreting assessment criteria differently (Stolpe *et al.*, 2021)
- Lack of clarity on the specific roles of faculty, supervisors, and external examiners (Varshney, 2021); and
- Experience or inexperience of examiners (Jansson *et al.*, 2019).

Nonetheless, overcoming these challenges requires proper communication between all role players about the specific criteria that are used to assess students' research dissertations (Smyth *et al.*, 2012; Poon, 2019). Lastly, finding and balancing time to meet the competing demands of postgraduate coursework studies with full-time employment was found to be a significant barrier for certain students. Unfortunately, this is a universal problem for students who are enrolled for postgraduate coursework programmes while they are in full-time employment (Moreau & Leathwood, 2006; Evans *et al.*, 2014; Richardson *et al.*, 2014). Inevitably, students who fail to adjust to such competing priorities may opt to exit their study programmes, thus increasing drop-out rates in the current MCPEM at UJ. This problem is particularly difficult to resolve, especially as there are considerable personal variations in the circumstances of affected students (Barron & Anastasiadou, 2009). Nonetheless, the identification of specific barriers and challenges that students have experienced enables the transition to move from a generic curriculum to a more responsive pedagogy with relevant interventions. Possible measures worthy of exploration for such a responsive pedagogy include supervised group learning (D'Alessandro & Volet, 2012); special lectures with flexible timetables (Prinsloo, 2019); better time management (Vicencio & Banaag, 2019); and the introduction of distance education learning models and improving the effectiveness of blended learning strategies (Graham *et al.*, 2019). Implementing these measures effectively is highly recommended because doing so is in line with Priority No. 2 in UJ's Strategic Objectives, which emphasise the utilisation of digital technologies to enhance and bring about flexible learning opportunities that can lead to positive experiences and higher success rates for students (University of Johannesburg, 2026).

## 6. Conclusions and Recommendations

In this chapter, the satisfaction of students on how they experienced various aspects of teaching and learning in the MCPEM has been assessed. Similarly, the research examined the value that students attach to the programme as well as the barriers and challenges that they encountered in the completion

of their postgraduate studies. By making use of a mixed-methods research design, primary data were gathered by means of questionnaire-administered surveys as well as FGDs.

Based on the demographics generated from the data, 23 students responded to our assessment, comprising nearly 62% female students. Such demographics are in line with institutional demographics which show that female students number relatively more than male students. The dominant age category comprised individuals aged 30 to 39 years (72%) and the majority (77%) of them were in full-time employment. This finding shows that offering the MCPEM at UJ contributes towards the academic and professional competencies that are needed in the environmental management sector and other economic sectors in South Africa.

Other findings generated in this study provide further insights to inform interventions for increasing the general satisfaction of students enrolled for the MCPEM at UJ, thus contributing towards their success rates. Generally, higher percentages of students were satisfied with the MCPEM, with the exception of a few aspects that warrant redress. The proportions of students who expressed satisfaction ranged from 50% to 61% amongst respondents who were in strong agreement with statements that the teaching was appropriate and relevant to their learning and professional training needs. Similarly, the supervision of students was effective except for a few cases where students experienced difficulties. In addition, the qualitative data generated from FGDs revealed specific areas of strength in this programme while areas that need more attention were highlighted. Given these findings, it can be stated that whereas the teaching, learning, and the supervision support is student-centred, there is a need to address certain pitfalls. For instance, few (5%) respondents expressed some dissatisfaction about the limited coverage of topics such as waste management, ESG, and climate finance in the MCPEM. Therefore it is imperative for course content to remain current and continuously updated to reflect new and emerging topics, as well as developments within the environmental management sector in South Africa and abroad.

The value and benefits of completing this programme successfully were acknowledged by respondents. Most respondents strongly agreed that they have acquired various competencies such as theoretical and professional knowledge relevant to the environmental sector (67%), ability and eligibility to apply for professional registration in South Africa (61%) and the necessary skills to manage and resolve environmental problems (56%). When students are appreciative of the value of the programme, this is a reflection of how they perceive the quality of the teaching and learning environment, course content, and its relevance to their professional careers.

In terms of barriers experienced by respondents as they studied for this programme, the results revealed mixed experiences. According to the evidence gathered from the questionnaires, only a few respondents experienced some of the specified challenges. On the contrary, qualitative data were more incisive in delineating some of the challenges experienced by students. Topmost amongst these difficulties included supervision constraints, competition between time allotted to formal studies against the pressures that come from full-time employment as well as the need to update course curriculum to be in line with new topics in the field of environmental management. Given these barriers, a more blended teaching and learning approach is recommended whereby the existing teaching model that requires campus-based physical interaction may be complemented and reinforced by technology-mediated and Web-enhanced learning platforms to accommodate the varied teaching and learning needs of students.

In terms of future research efforts, the following areas are recommended. To widen the generalisability of the results, a higher number of students must be included in future student satisfaction research. Similarly, an in-depth case study on the barriers and challenges experienced by both supervisors and students is recommended. Lastly, given that student satisfaction is dependent on perceptions, studies that can investigate satisfaction levels according to the specific year of graduation may shed light on how they change or remain the same over time.

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## DATA VALIDATION FOR LIKERT SCALE RESPONSES

| | | N | Mean | SD |
|---|---|---|---|---|
| 16.1 | Learning outcomes were made clear to students | 21 | 4.33 | 1.197 |
| 16.2 | A variety of learning activities were used to help me achieve the module learning outcomes | 21 | 4.19 | 1.209 |
| 16.3 | Teaching and learning materials supported learning and the acquisition of environmental management knowledge and skills | 21 | 4.24 | 1.179 |

(*Continued*)

(*Continued*)

| | | N | Mean | SD |
|---|---|---|---|---|
| 16.4 | The concept of sustainability assessment, critical thinking, and integrated environmental management permeated all teaching and training | 21 | 4.19 | 1.250 |
| 16.5 | Environmental management was taught as a distinct study field, process of decision-making and a professional field | 21 | 4.19 | 1.209 |
| 16.6 | The lecturers incorporated current issues and practical examples into the discussions, thus making the course relevant to the professional world | 21 | 4.14 | 1.195 |
| 16.7 | The lecturers used varied teaching methods to explain certain concepts | 21 | 4.19 | 1.167 |
| 16.8 | The lecturers gave appropriate feedback which supported my learning | 21 | 3.90 | 1.300 |

| | | | |
|---|---|---|---|
| 18.1 | Choosing or being allocated a research supervisor was easy for me | 4.25 | 1.333 |
| 18.2 | The supervisors gave me all the necessary information on tasks to be completed for my research project | 4.20 | 1.240 |
| 18.3 | I received adequate guidelines on how to conduct my literature review | 4.30 | 1.174 |
| 18.4 | My supervisors always communicated clearly on what was expected and gave me feedback timeously | 4.20 | 1.152 |
| 18.5 | Writing the research proposal was easy for me | 3.80 | 1.056 |
| 18.6 | Scientific writing was easy for me | 3.75 | 1.070 |

| | | | |
|---|---|---|---|
| 18.7 | Gathering, analysing, and interpreting my primary data collected was easy | 3.80 | 1.152 |
| 18.8 | Writing and finalising the minor dissertation for examination was easy | 3.65 | 1.137 |
| 18.9 | The necessary precautionary measures to prevent plagiarism in my assignments and manuscripts were clearly communicated to me | 4.20 | 1.196 |
| 18.10 | After the first external examination of my dissertation I was given adequate feedback and guidelines on what to do next | 4.25 | 1.209 |
| 18.11 | The findings from my research were published in a journal or as conference proceedings | 3.75 | 1.713 |
| 18.12 | I attended at least one conference or symposium to present my research findings | 3.35 | 1.814 |
| 18.13 | The manner in which I experienced the research project and the supervision received supported and stimulated further interest to investigate other research problems in environmental management and allied fields | 4.10 | 1.119 |

| | | | | |
|---|---|---|---|---|
| 20.1 | Assessments done by writing research assignments were the most difficult | 21 | 2.62 | 1.071 |
| 20.2 | Assessments by means of syndicate group assignments were difficult to complete | 21 | 2.48 | 1.078 |
| 20.3 | Assessments done through semester tests were difficult | 21 | 2.48 | 1.123 |
| 20.4 | Assessments that were done by oral presentations of certain topics and research proposals were difficult | 21 | 2.24 | 0.831 |

(*Continued*)

(*Continued*)

| | | | | |
|---|---|---|---|---|
| 20.5 | Assessments done by final examinations at end of semester were difficult | 21 | 2.71 | 1.146 |
| 20.6 | Closed-book assessments were more difficult than open-book assessments | 21 | 2.67 | 1.111 |
| 20.7 | Open-book assessments were more difficult than closed-book assessments. | 21 | 3.00 | 1.095 |
| 20.8 | All assessments were extremely difficult | 21 | 2.29 | 0.902 |
| 20.9 | The lecturers were fair, consistent, and trustworthy in all of the assessments done | 21 | 4.10 | 0.995 |
| 20.10 | The final total mark I received at the end of the programme reflects my diligence and hardworking throughout the programme | 20 | 3.85 | 1.348 |

| | | | | |
|---|---|---|---|---|
| 23.1 | With this qualification it was easy for me to find work in the environmental management sector | 21 | 3.43 | 1.287 |
| 23.2 | With the qualification I received work in a different economic sector | 20 | 3.10 | 1.447 |
| 23.3 | The lecturers had adequate practical knowledge about the environmental management sector, thus preparing us for the world of work. | 21 | 4.24 | 1.261 |
| 23.4 | Knowledge gained from the programme enabled me to apply successfully for my professional registration which is mandatory in South Africa | 21 | 4.00 | 1.225 |

| | | | | |
|---|---|---|---|---|
| 23.5 | Knowledge and skills acquired from the programme helped me to resolve environmental management tasks at my workplace | 21 | 4.14 | 1.108 |
| 23.6 | With the training I received from both the theoretical and the research component of the programme I have been able to register for a PhD degree | 21 | 3.05 | 1.627 |

| | | | | |
|---|---|---|---|---|
| 25.1 | I found the learning content quite challenging partly because of my inadequate knowledge of environmental management in my honours qualification | 21 | 2.00 | 1.095 |
| 25.2 | Because I was in full-time employment it was difficult finding time for studies and doing my research effectively | 21 | 3.05 | 1.284 |
| 25.3 | I found it difficult to submit my assignments and other work timeously | 21 | 2.19 | 1.123 |
| 25.4 | Time allocated to lectures was inadequate | 21 | 2.43 | 1.121 |
| 25.5 | I experienced financial difficulties during my study period to pay fees and research expenditures | 21 | 2.19 | 1.365 |
| 25.6 | Lecturers were not always available for consultation on some aspects of the teaching, learning and research | 21 | 1.86 | 0.910 |
| 25.7 | Undertaking research and literature independently was very difficult for me | 21 | 2.14 | 0.727 |

(*Continued*)

(*Continued*)

| | | | | |
|---|---|---|---|---|
| 25.8 | Scientific writing required in the programme was not easy to master and was required throughout the programme | 21 | 2.57 | 0.926 |
| 25.9 | I was unable to complete the whole course in record time thus adding unnecessary time to complete the degree programme. | 21 | 2.38 | 1.396 |

# Chapter 2

# Integrating Formal and Out-of-Classroom Learning in a First-Year Geology Field School: A Reflective Pedagogical Approach

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## Abstract

Geological fieldwork is widely acknowledged as a critical component of Geoscience education, yet first-year students often struggle to apply classroom knowledge to the complexities of natural environments. This challenge is magnified in the South African context, where many students enter university from under-resourced educational backgrounds with limited exposure to scientific field excursions, hands-on learning, or the outdoors. In response to these epistemological, cognitive, and pedagogical challenges, this chapter examines a suite of interventions implemented to integrate formal and out-of-classroom curricula within a five-day first-year Geology field school. In this study, we reflect on student feedback and facilitator observations of interventions that included: (1) a pre-field school assignment to build conceptual familiarity with the geology of the field

area; (2) field-based mini lectures using maps and stratigraphic terminology to contextualise observations; (3) the introduction of laboratory-based materials such as polished rock specimens and photomicrograph charts to support outcrop observations and interpretation; (4) guided question sheets to scaffold observation and reasoning; and (5) modular field exercises to break down complex tasks into manageable activities aligned with students' classroom experiences. Drawing from iterative implementation, student feedback, and reflections of teaching staff, this chapter evaluates the effectiveness, limitations, and contextual relevance of these methods. Findings highlight the value of early scaffolding, translational tools that bridge laboratory and field environments, and modular assessments in supporting student engagement and learning. However, there were challenges that emerged around workload feasibility, assessment overlap (i.e., deploying the same assessment tool at different geological localities to gauge student proficiency, without discouraging creativity and encouraging a narrow, model-driven mindset amongst students), and the risk of over-structuring student enquiry.

**Keywords:** Cognitive Scaffolding, Curriculum Integration, Field-Based Learning, Global South Education, Inclusive Pedagogy, Student Engagement

## 1. Introduction

Geological fieldwork is the practice of observing, documenting, and interpreting geological features and processes directly in their natural settings. This can be achieved in places such as bedrock outcrops, quarries, road cuts, riverbeds, and caves, amongst others (Figure 2.1). It has been argued that fieldwork is the core of the Geology discipline, where any ideas or truths about Earth can be studied, understood and proven (Mondlane & Mapani, 2002; Butler, 2008; Kelso & Brown, 2009; Stokes & Boyle, 2009). Therefore, geological fieldwork plays a critical role in the training of undergraduate Geology students because it serves as a bridge between theoretical knowledge taught in the classroom and laboratory, and the complex, often unpredictable realities of geological formations in the natural environment. While

students may initially engage with rocks through hand specimens in the laboratory sessions, colloquially termed "practicals", fieldwork provides exposure to outcrops *in situ* for a much deeper understanding of geological processes (Butler, 2008; Esteves *et al.,* 2013). Laboratory settings limit the students' practical interaction to the observation of texture, grain size, and mineralogy of hand specimens without a clearer understanding of the relationships of those hand specimens in their natural context. Fieldwork enables the extension of observations to larger-scale features such as grain size and facies changes, bedding, folds, faults, and other deformation structures, as well as active processes when settings allow. Thus, field sites become a natural laboratory where students can apply and contextualise their classroom learnings in meaningful ways that develop their problem-solving skills and enhance their application of the scientific method (Stokes & Boyle, 2009). Research consistently supports the view that field-based learning deepens students' understanding of geological processes, providing an added pedagogical dimension that classroom- and laboratory-based teaching alone cannot replicate (Elkins & Elkins, 2007; Esteves *et al.,* 2013; Fonck, 2024).

It is expected for a Geology undergraduate programme in South Africa, and globally, to include a series of field schools ranging from single- to multi-day excursions. These field experiences are a foundational aspect of Geoscience education and vary widely in duration, structure, frequency, and teaching approach. Despite their value, field schools are not uniform in practice and require careful design to be effective, particularly for first-year students conducting geological fieldwork for the first time. These students are transitioning from studying simplified, carefully selected textbook examples that often feature idealised examples and annotated sketches and photographs, to far more complex, unlabelled geological realities, where contradictory features often coexist; interpretation is, thus, challenging without detailed guidance.

The transition from the lecture room to the field represents both a pedagogical opportunity and challenge, as students frequently struggle to connect textbook knowledge and lectures with real-time field observations (Esteves *et al.,* 2013; Dolphin

*et al.*, 2019). Moreover, each field locality presents a different geological setting characterised by different lithologies, structural features, anthropogenic influences, and scale, for example, which complicates the application of uniform teaching strategies (Figure 2.1). Field instructors must contextualise *in situ* geological complexities relatable to textbook examples, employing diverse methods to accommodate not only geological variability but also differences in student learning preferences and physical comfort levels (Butler, 2008; Chiarella & Vurro, 2020; Giles *et al.*, 2020). Challenges unrelated to Geology, such as discomfort with the outdoor environment, the weather, phobias, and physical fatigue further complicate teaching and engagement in the field.

Although undergraduate Geology programmes are offered at most major universities in the country, Scholarship of Teaching and Learning (SoTL) research that addresses the pedagogical challenges of teaching geological field techniques to first-year students in a South African context has not been previously undertaken. This is in spite of the major pedagogical challenges experienced in university Geology classrooms because of the systemic inequalities in schooling, access to educational resources, and prior exposure to fieldwork, all of which can impact students' learning experiences. The Geology Department at the University of Johannesburg, and by extension, the Geology degree programme, evolved from serving an exclusively white, male student demography to a predominantly black, gender-diverse student demography from mostly rural and township schools, many of whom had limited or no prior exposure to field trips or experiential outdoor learning. This demographic evolution of the student population in the Geology degree programme was accompanied by several challenges: increased class sizes, greatly varying knowledge levels and general under-preparedness for university education, out-of-classroom learning (dis)abilities, and reluctance of students to speak up, voice opinions, or ask questions in a group environment. These challenges affected logistical preparation and teaching of the first-year field school module, which necessitated change over the years. The absence of context-specific literature or shared best practices has meant that we, the teaching staff responsible for the successful and impactful execution of the field school, have had to rely heavily on internal trial and error experimentation to shape our approach.




**Figure 2.1:** Photographs showing examples of field settings. (A) Students observe and measure outcropping bedrock in a field where the geology differs significantly from the idealised textbook examples. Drone photo by Tebogo Makhubela. (B) Students making geological observations inside a cave to give them an experience of working underground, a common practice for geologists. Photo by Mathabela Tsikoane (with permission).

With the aim of improving the first-year Geology field experience and outcomes, a core team of teaching staff considered a variety of approaches. How could we effect a change in the first-year field excursion experience that benefits the evolving student body, and maximises the teaching staff input, making use of individual skillsets amongst staff? This chapter reflects on several years of teaching geological field techniques at the first-year field school course within a South African university context. In particular, we examine our efforts to integrate formal and out-of-classroom curricula in the field. This includes using familiar laboratory tools and materials such as polished hand specimen samples and their associated photomicrographs in field settings to bridge the gap between the controlled campus environment and the more challenging field experience. Guided questions tailored to specific localities were also used to scaffold students' engagement with unfamiliar outcrops (Van der Stuyf, 2002). By sharing both successes and limitations within a South African higher education context where many students come from disadvantaged educational backgrounds, we hope to offer insights and practical guidance to other Geoscience educators facing similar challenges in their teaching practice.

## 2. Literature Review: Conceptual and Pedagogical Background

Fieldwork aligns strongly with experiential learning theory, particularly as articulated by Kolb (1984; Kolb & Kolb, 2009), who emphasised learning as a cycle involving concrete experience, reflective observation, abstract conceptualisation, and active experimentation. In the field, students move continuously through this cycle: they observe geological features, reflect on their significance, link them to theoretical knowledge, and test their interpretations through sketching, discussion, and measurement (Butler, 2008). The field setting encourages students to make sense of what they see based on prior textbook-derived knowledge, in-field peer interactions, and guidance from instructors (Butler, 2008; Stokes & Boyle, 2009). Unlike in a traditional classroom setting, learning and understanding is co-created via on-site explanations and discussions, deepening as

students reframe their observations through multiple interpretive passes of the field-based learning cycles.

Geological fieldwork is inherently a form of experiential, place-based learning (PBL), which is an approach that is deeply rooted in the local context as a starting point to teach concepts (Semken *et al.,* 2017; Goodlad & Leonard, 2018). Mogk and Goodwin (2012) demonstrate that PBL supports the engagement and retention of underrepresented students, including indigenous learners, by grounding Science in more familiar cultural and environmental settings. It also enhances students' "sense of place," encouraging identity formation, environmental stewardship, and interdisciplinary thinking (Semken *et al.,* 2017). Importantly, culturally responsive assessment practices are essential when implementing PBL. Assessments must consider local knowledge systems, language and syntax variations (Semken *et al.,* 2017). This ensures that evaluation tools do not unintentionally exclude or misrepresent the learning gains of diverse student bodies.

John Dewey's experiential learning philosophy remains a foundational influence on context-responsive and applied learning education. Dewey emphasised that knowledge is actively reconstructed by learners based on their prior experiences (which is limited in this case of fieldwork exposure), and not passively received (Alanazi, 2016). In this view, meaningful learning requires context, activity, and reflection. Integrating formal instruction with out-of-classroom experiences aligns with this view by enabling students to move beyond the abstract, decontextualised content towards applied understanding through lived interaction with the geological environment. Traditional education, by contrast, often relies on didactic instruction and highly structured laboratory-based learning, which can limit learners' capacity to apply scientific knowledge meaningfully (Awan, 2021; Kincheloe, 2016). This mode of delivery, while common practice in teaching and learning of foundational knowledge, tends to present Science as a fixed body of facts rather than an evolving, enquiry-driven process. Consequently, it may unintentionally distance students from the practices and thinking of actual scientists (Butler, 2008; Stokes & Boyle, 2009).

Braund and Reiss (2006) argue that formal in-classroom Science teaching often reflects a narrow presentation of Science that is dominated by simplified content limited to classroom or laboratory settings. In contrast, field-based and out-of-classroom learning fosters experiences that are more aligned with what scientists, in this context, geologists, do in practice. These experiences enhance authenticity and relevance, allowing students to see scientific enquiry as a tool for engaging with real-world challenges. Field settings also provide access to unique materials and large-scale phenomena that cannot be replicated in the laboratory (Braund & Reiss, 2006). *In situ* geological settings not only improve conceptual understanding but also build confidence and practical skills that are critical for scientific literacy (Chen *et al.*, 2025), as well as life-skills. Increased engagement with teaching staff and peers and, thus, enhanced motivation, are consistently reported as benefits of out-of-classroom learning. For example, student interest in Science tends to a decline in formal schooling environments, but is often reinvigorated through museum visits, field excursions, or science centre experiences (Braund & Reiss, 2006). These informal settings stimulate curiosity and foster effective connections with scientific content, and students describe such experiences as enjoyable, socially enriching, and intellectually stimulating (Braund & Reiss, 2006).

Despite its advantages, integrating out-of-classroom learning into formal curricula remains challenging. One major obstacle is the rigidity of traditional university structures, which emphasise content coverage, standardised testing, and classroom seat time (Braund & Reiss, 2006; Goodlad & Leonard, 2018). These constraints can marginalise field-based experiences, positioning them as extracurricular or low-stakes, thereby reducing their pedagogical impact.

## 3. Challenges in Teaching Geological Field Techniques

Teaching geological field techniques presents a variety of challenges that are grouped into three broad categories for the purposes of this chapter: epistemological and cognitive challenges

related to the nature of geological knowledge in the field; pedagogical challenges related to field-based teaching practices and engagement; and non-academic contextual challenges shaped by the physical realities of field environments, and inclusion of students' needs in this exposed learning environment (Figure 2.2).

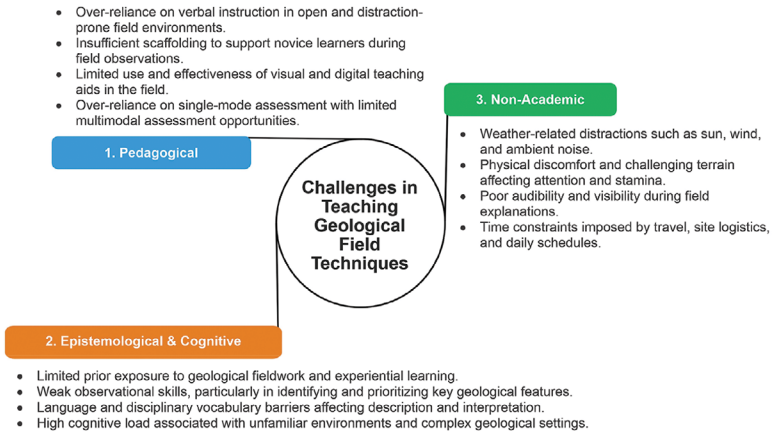



**Figure 2.2:** Common factors that contribute to the challenges of teaching geological field techniques.

## 3.1. Epistemological and Cognitive Challenges

First-year students often enter university with little to no exposure to field-based learning (Butler, 2008) or the understanding of the benefits of such. This is even more prevalent in the Geosciences, as Geology is not a stand-alone subject at school (secondary education) in South Africa, and only briefly taught in the Geography curriculum. Thus, the first-year understanding of Geology is initially shaped by simplified theoretical models and highly curated textbook diagrams often paired with carefully selected and annotated photographs labelled "what a geologist sees" (example, Figure 2.3). These representations do provide essential conceptual scaffolding (Van der Stuyf, 2002; Van de Pol *et al.*, 2010), but they can also create unrealistic expectations of what geological features "should" look like (Stokes & Boyle, 2009; Dolphin *et al.*, 2019). When students are confronted with real outcrops in the field where features may

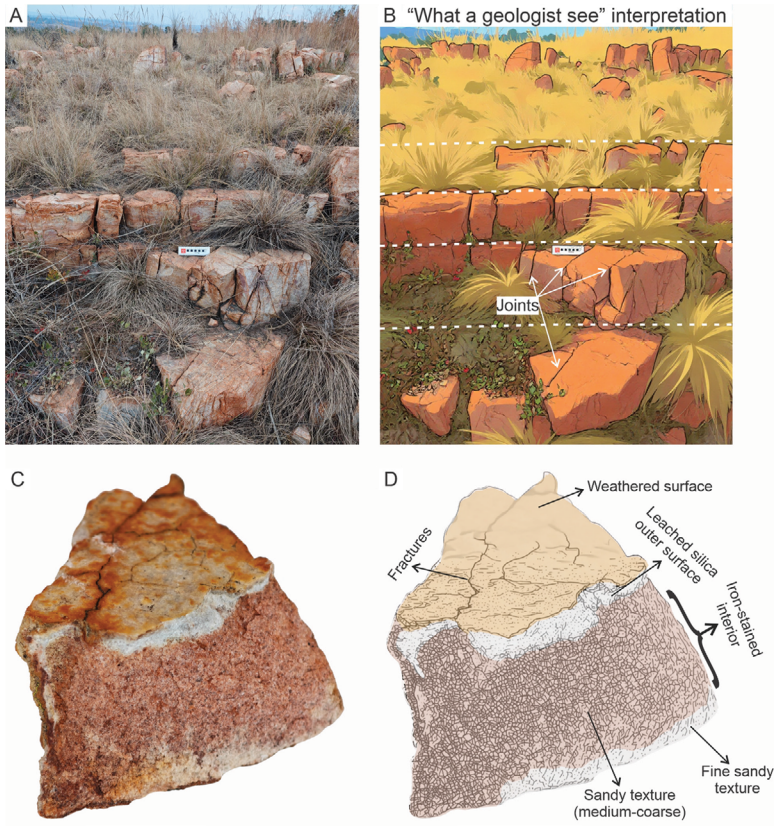



**Figure 2.3:** Example of geological interpretation of field observations. (A) Photograph showing outcrops of quartzite. (B) Simplified interpretation of the geology shown in the photograph. The dashed horizontal lines mark the individual beds of the sandstone, which are a primary sedimentary feature that students should be able to identify on outcrops in the field together with later features such as joints. (C) Photograph of hand specimen showing a weathered surface and a fresh surface of the rock. (D) Sketch of the hand specimen with annotations that describe the texture and features. Students are expected to make such sketches and interpretations in field notebooks when making observations in the field. Photos by Tebogo Makhubela.

be weathered, partially exposed, or structurally complex, they frequently struggle to identify key characteristics without direct guidance (Elkins & Elkins, 2007). Many students are surprised to find that geological features do not "announce" themselves, but must be interpreted from subtle, contextual clues (Esteves *et al.,* 2013; Dolphin *et al.,* 2019). This creates cognitive dissonance that is especially prominent when students attempt to transition from two-dimensional learning of the classroom to three-dimensional observation and interpretation in the field (Butler, 2008; Stokes & Boyle, 2009; Thornbush, 2014). Developing spatial awareness, visual estimation of scale, and an ability to synthesise various observations into coherent geological narratives requires time and guided practice. Without structured support, students may become overwhelmed or disengaged (Elkins & Elkins, 2007; Giles *et al.,* 2020).

## 3.2. Pedagogical Challenges

From a teaching perspective, geological fieldwork is challenging because it is inherently site-specific and always requires an element of improvisation, no matter the amount of preparation for that specific site or the number of annual visits. Unlike classroom teaching, where content delivery can be standardised, field instruction must constantly adapt to the geology and context of each locality (Butler, 2008; Dolphin *et al.,* 2019). Different sites present different lithologies, structures, and geological histories, making it difficult to apply a uniform teaching method across all the localities comprising a given field school. Furthermore, natural outcrops are often "incomplete" or "imperfect" and hardly resemble textbook examples. Between visits, erosion or damage to the preferred teaching outcrop may have occurred, or vegetational growth impacts on the visibility. Weather on the day of the field visit may override all efforts to ensure adequate teaching and learning. Thus, field instructors must be prepared to shift between explanatory modes such as demonstration (show-and-tell to enhance knowledge), questioning (to stimulate critical thinking), discussion (to promote peer-to-peer learning), and sketching (to assist with three-dimensional (3D)

visualisation) depending on the geology encountered and the students' responses and their zone of proximal development as assessed by the instructor (Vygotsky, 1978; Elkins & Elkins, 2007; de Barros *et al.*, 2012; Hedegaard, 2012).

The spatial arrangement of students in the field also limits the instructor's reach because fieldwork often requires moving between small groups or individuals and is best done by multiple instructors. This creates asymmetries in attention and information shared, with some students receiving more direct engagement than others (Dolphin *et al.*, 2019). Moreover, field leaders must simultaneously manage time, group dynamics, student safety, and logistical constraints, all while maintaining instructional clarity, as they often know the localities visited more than the other instructors involved. Balancing these roles can dilute the depth of teaching that each student receives (Butler, 2008; de Barros *et al.*, 2012), and students may lack the confidence to ask for assistance.

Another dimension of difficulty lies in assessment and real-time feedback. Evaluating student understanding during fieldwork is complex because of the informal and interactive nature of the environment (Stokes & Boyle, 2009). Immediate feedback is invaluable, but formative assessment tools such as field notebooks and verbal responses are time-intensive to evaluate in real time (Butler, 2008). Summative assessments may miss the nuanced learning that occurs during observation, interpretation, and discussion in the field (Elkins & Elkins, 2007).

### 3.3. Non-Academic Challenges

Teaching field techniques is further complicated by non-geological factors that affect students' ability to participate meaningfully (Chiarella & Vurro, 2020; Giles *et al.*, 2020). Weather conditions such as heat, wind, or rain can limit mobility, affect concentration, and shorten the learning window (Stokes & Boyle, 2009). Rugged terrain, long walking distances, or physically demanding conditions can disproportionately affect students with lower fitness levels and those unaccustomed to outdoor environments (Chiarella & Vurro, 2020; Giles *et al.*, 2020).

Fatigue, dehydration, and inadequate nutrition during multi-day field excursions can also compromise student participation and learning outcomes. Furthermore, unequal access to field-appropriate gear such as boots, sun protection, or outdoor clothing can widen disparities in learning experiences amongst students from different socio-economic backgrounds (Butler, 2008; Giles *et al.,* 2020). Phobias of insects and allergies to plants can further exasperate the negative experience. In addition, students may feel a sense of disconnect with the unfamiliar outdoor environment, a lack of belonging, and general discomfort with being out of their comfort zone.

## 4. Teaching Context and Background

The compulsory credit-bearing first-year *Geological Field Techniques* module (herein referred to as the field school) in our department is presented during the university holidays before the start of semester 2. Although the field school is classified as a semester 1 module, it has no scheduled contact time with the students during semester 1. The field school follows the initial first-year module called *Minerals, Rocks and Earth Dynamics*, which is an introductory general Geology module taken by first-year Geology major students and second-year Civil Engineering students during semester 1. The introductory module broadly introduces students to most Geology topics and theoretical concepts that are dealt with in greater detail in subsequent modules of the Geology degree (semester 2, and study years 2 and 3). The learning outcomes of the field school module are for the students to:

- Identify and describe rocks in the field.
- Appreciate the value of field work.
- Classify the rocks observed into their lithostratigraphic groupings.
- Make geological observations and record them in a coherent way in their field notebook.
- Use geological field equipment.
- Make notes about the relationship between geological features and the environment.

The field school is conducted annually over five consecutive days with at least seven hours per day being in the field. The season is mid-winter on the South African Highveld, thus, with generally sunny days and moderate temperatures, and far cooler evenings; should the wind blow, the conditions can be very chilly. To promote cohesion within the group and establishment of peer relationships, students, teaching staff, and postgraduate assistants reside at a camp facility near the reserve where the field school is conducted. The camp provides full board, with meals and shared dormitory accommodation equipped with running water and serviced ablutions.

Students are required to wear appropriate field gear and to manage their fieldwork materials and equipment. Depending on the class size, four to six teaching staff accompany the group, as well as one or two postdoctoral research fellows seeking to gain experience in teaching in the field. The teacher-to-student ratio is generally 1:5. The core field-based teaching staff (the authors) have remained fairly consistent for the last five years and are not necessarily the same staff as the in-class lecturer or practical class demonstrator. The teaching staff includes members with diverse backgrounds in geological research and expertise, such as Sedimentology, Economic Geology, Mineralogy, Geochronology, and Structural Geology. This diversity benefits students by exposing them to various fields of Geology and illustrating how different techniques are used during fieldwork.

Each morning, students are transported to the field area, where they engage in seven to eight hours of fieldwork across multiple stops or localities (generally two per day), depending on the day's itinerary and required learning outcomes; a packed lunch is provided. During the evenings, students engage in a two-hour long activity after dinner. The evening activities include PowerPoint lectures delivered by teaching staff on the broader geology of the sites visited and the geology of South Africa, informal discussions about careers in geology and strategies for academic success, and a field-themed quiz competition on the final evening. The quiz night also serves as a structured peer-learning activity, promoting collaborative reflection on the week's learning (see below).

Students are provided with all essential fieldwork materials and equipment, including a hand lens, measuring tape, grain size comparison chart, stationery, and a field notebook. The students are required to record all field-based lectures, discussions, notes, sketches, and assignments in their field notebooks, and are instructed to respect their books (with a mark given for neatness). Well-structured and informative field notebooks are vital to a working geologist, capturing the field observations and findings required for input into digitised maps and geological models. The field notebooks are assessed each evening by the teaching staff, with marks and comments provided to each student in their books; the intention is to encourage progression during the module. During the day, the teaching staff provide real-time guidance to sketching and annotation, enabling students to improve their observation and recording skills. The notebooks and a final mapping assignment in the field provide the combined final assessment mark for the module.

The students also receive a comprehensive, hard copy field guide, which contains the daily schedule, assessment criteria, procedural guidance for recording field observations, rock classification schemes, and appendices. The guide is designed to scaffold student learning by blending theoretical instruction with practical application (Van der Stuyf, 2002), making it an essential bridge between formal coursework and experiential learning.

The field school was previously (2007-2017) conducted at the Vredefort Impact Crater World Heritage Site, approximately 200 km south of Johannesburg. While this location is of significant geological importance, its geology was ultimately deemed too complex for first-year students at the introductory level. The rocks in this area have undergone intense deformation because of the meteorite impact event, exhibiting features such as overturned stratigraphy, shatter cones, brecciation, high-pressure mineral phases, and the presence of pseudotachylite formed by impact-generated melt that obscure original bedding and structural orientations (Reimold & Gibson, 1996). These characteristics, while fascinating, presented interpretive

challenges that exceeded the cognitive readiness of first-year students and distracted them from the basic rock descriptions that they needed to focus on for this field school.

In an effort to align the field module more closely with the learning needs of first-year students, in 2018 we relocated the field school to the Krugersdorp Nature Reserve, situated approximately 40 km west of Johannesburg. This site offers a more accessible geological context of the Witwatersrand and Transvaal Supergroups, two significant geological formations in South Africa with unique characteristics and history (including the gold rush). These rock formations provide suitable field-based teaching sites for introducing foundational field skills such as lithological description, basic geological measurements, and mapping. Ormond (2019) conducted her Master of Science (MSc) research at the Krugersdorp Nature Reserve and, thus, could provide a detailed understanding of the geology of the nature reserve beyond the identification of the outcropping rock types. The teaching staff undertook site visits to determine the most appropriate localities required to match the field school learning outcomes.

## 5. Teaching Approaches and Interventions

To address the epistemological, and cognitive as well as the pedagogical challenges encountered in teaching geological field techniques to first-year students, we developed and implemented a suite of interventions aimed at integrating formal curricular content with informal, place-based field experiences. These interventions were designed and introduced at different times over a six-year period to facilitate coherence between the controlled learning environments of classrooms and laboratories and the inherently complex and dynamic conditions of the natural environment, i.e., the field. The five integrated approaches that were central to this effort are: (1) pre-field school assignments, (2) field-based lectures, (3) use of laboratory tools and materials in the field, (4) guided observation through structured questioning, and (5) modular, activity-based field assignments. The integrated approaches are detailed below, with reflection on the successes following.

### 5.1. Pre-field school assignment for bridging theory and field readiness

The first step in this integration strategy involved assigning students a pre-field school research task, disseminated via our university's learning management system (initially Blackboard, now Moodle). This assignment, distributed several weeks prior to the start of the field school, required students to conduct independent research on the general geology of the areas where the field school takes place. The goal of the pre-field school assignment was to expose students to some foundational understanding of the stratigraphy, lithological units, and regional geological framework that they would encounter in the field.

### 5.2. Field-based lectures for contextualising and reinforcing theoretical knowledge

Geological fieldwork excursions inherently include structured mini lectures presented by the teaching staff, conducted on-site at every locality visited (Figure 2.4). The field-based introductory lecture



**Figure 2.4:** Lectures in the field are an intrinsic part of the teaching experience. Photograph by Subrahmanya Kondepudi Venkata (with permission).

serves to remind the students of the classroom and practical class knowledge acquired during semester 1 while introducing some key concepts not yet taught such as the stratigraphic classification scheme, i.e., *Supergroup*, *Group*, *Formation*, and *Member*, required for use during the field school. Fundamental skills required for effective field documentation are addressed, including instruction on determining and applying appropriate scale when sketching, and techniques for rendering accurate field drawings in their notebooks. In addition, the morning lectures on subsequent days included formative assessment feedback that was informed by the outcomes of the previous day's work.

## 5.3. Using laboratory materials in the field for enhancing observational skills

To further bridge formal and informal learning settings, we introduced the use of laboratory tools and familiar materials directly into the field school. This included on-site sharing of polished hand specimens of rocks collected from each of the localities visited. These polished specimens, similar to the ones used during semester 1 practical sessions, provided clearer surfaces that allowed for observation of mineral textures and fabrics that are often obscured in weathered or freshly broken samples in the field (Figure 2.5). Polished sections revealed compositional details that allowed students to more confidently compare *in situ* exposures with familiar reference material. Additionally, thin sections of the same rock samples used to make polished hand specimens were prepared and used to generate high-quality photomicrographs through optical microscopy. These photomicrographs were printed in A4 format, laminated, and distributed in multiple sets for student use during field activities.

## 5.4. Guided observation through structured questioning

Recognising that students often struggle with field observations and interpretation because of unfamiliarity and cognitive overload (novelty space) (Mogk & Goodwin, 2012), we developed guided question sheets tailored to each field locality (see Appendix for example). These sets of questions were designed to scaffold

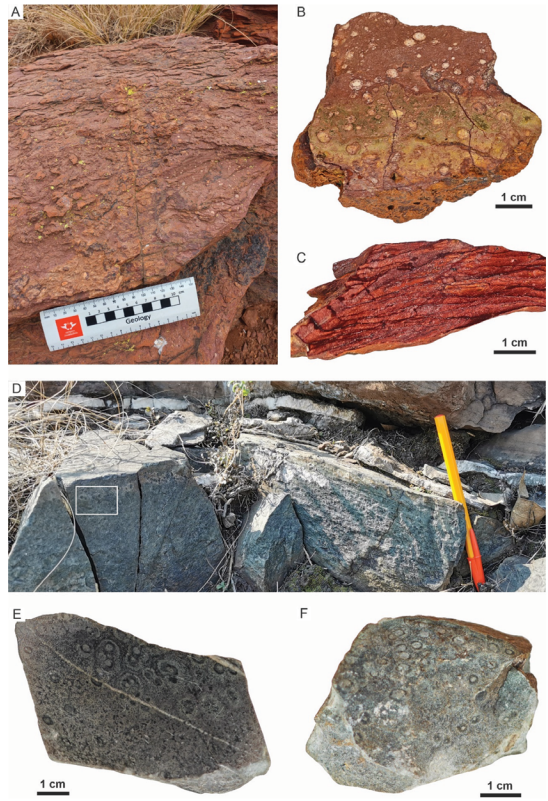



**Figure 2.5:** Examples of polished hand specimens of rocks to clearly display rock textures enabling accurate observations by students. (A) Outcrop of the Witwatersrand's Crown Formation lava with amygdales that are hardly noticeable to an inexperienced eye such as those of first-year students. (B, C) Polished hand specimen from outcrop in (A) showing the rounded amygdales clearly as being part of the rock's texture (B) and lines (representing the intersection of a planar fabric, cleavage in this case, with the outer surface of the rock) that can be seen on the exterior surfaces of the outcrops (C). Also notice the original greenish colour of the rock prior to discoloration caused by oxidative weathering. (D) Outcrop of the Oaktree Formation tuff layer showing a lapilli texture (see white rectangle). (E) Polished hand specimen showing the lapilli texture much more clearly together with the finer matrix, which cannot be seen clearly in a freshly broken, unpolished hand specimen (F). Photos by Tebogo Makhubela.

student thinking (Van der Stuyf, 2002), beginning with basic descriptive tasks and progressing towards interpretive analysis. For instance, at a siliciclastic sedimentary outcrop, students were prompted to describe grain size, sorting, and rounding before being guided towards interpreting depositional environment and sediment transport mechanisms (see Appendix A). In contrast, questions at igneous or metamorphic localities focused on mineral assemblages, fabric, and textural relationships relevant to their petrogenetic histories. These tactics stress the importance in distinguishing observations from interpretations, a common struggle amongst many geology students regardless of their background. Therefore, we employed flexible strategies for distributing these question sets. In some instances, students received them at the start of their observation period; in others, we allowed them 30 to 40 minutes of independent exploration before introducing the structured prompts.

## 5.5. Modular field assignments

Historically, learning in our field schools was assessed solely through the submission of a field notebook, which was collected and marked daily. Feedback was based on observation quality (six marks), sketching accuracy (three marks), and notebook organisation (neatness) (one mark). While this method encouraged continuous engagement, it also placed a heavy burden on students to document large amounts of material without structured progression. To mitigate this, we restructured field assessment into modular, digestible activities that mimicked the structure and pacing of some laboratory sessions. Each field day included two to four targeted exercises in addition to standard notebook entries. These included (a) sketching a vertical profile of an ~2 m-deep trench using standardised stratigraphic log sheets, (b) constructing longer transect profiles (~200–250 m) to practice horizontal scaling and correlate outcrops, and (c) creating cross-sectional profiles across an erosional scarp in the notebook, requiring students to apply scale and spatial reasoning without a pre-formatted template. This blended approach allows for the student to remain task-focused through structured guidance while maintaining their ability to express creativity in their thinking and reporting.

## 6. Evaluation and Reflections on implementation

The evaluation and reflections presented in this section are grounded in Schön's Reflective Practice, specifically drawing on the concepts of reflection-in-action and reflection-on-action (Van den Bossche & Beausaert, 2011; Newman, 2020). This framework was particularly appropriate given the dynamic, unpredictable, and situated nature of field-based teaching, where pedagogical decisions are often made in real time in response to student engagement and emergent learning opportunities. Reflection-in-action occurred during the field school itself, as teaching staff continuously adjusted instructional strategies, pacing, and scaffolding in response to student needs and contextual constraints. Reflection-on-action took place after the field school or a specific field locality, through structured collective reflection amongst teaching staff, review of student work, and synthesis of field observations to evaluate the effectiveness of the implemented interventions. Rather than progressing through a linear sequence of reflection stages, our evaluative process emphasised professional judgement, responsiveness, and iterative refinement of teaching practice over a five-year period.

As with many reflective SoTL studies, this evaluation is subject to several limitations. First, the reflections presented here are primarily based on teaching staff perspectives, introducing the possibility of subjective bias and selective interpretation of outcomes. Although student feedback (informal during and after the field school), assessment outcomes, and observed participation patterns informed our reflections, the evaluation did not include formal triangulation through systematic student interviews, peer observation from external colleagues, or longitudinal tracking of learning outcomes beyond the field school. Second, reflection-in-action, while powerful, is inherently situated and contingent, making it difficult to fully disentangle pedagogical intent from contextual constraints such as time pressure, environmental conditions, and group dynamics. These limitations are acknowledged not as weaknesses, but as characteristic challenges of reflective enquiry in field settings.

Despite these constraints, Schön's Reflective Practice provided a robust and contextually appropriate framework for critically examining teaching interventions *in situ* and over time.

The pre-field school assignment, introduced as a preparatory research task, initially showed promise. It enabled students to familiarise themselves with the regional geology of the Witwatersrand and Transvaal Supergroups and introduced key terminology ahead of their physical engagement with the outcrops. This early exposure to the field context helped to reduce cognitive overload during the actual fieldwork and encouraged students to begin making conceptual connections between theory and practice. However, the long-term sustainability of this intervention proved problematic. Over time, student feedback revealed that the assignment added to their already overloaded semester 1 workload, especially given that the field module has no formally allocated slot in the timetable during that semester. While assigning the task over the holiday period provided a logistical solution, it inadvertently encroached on students' rest period. This was particularly problematic for students who were required to prepare for semester 1 supplementary examinations, which are typically scheduled for the week immediately following the field school. Thus, the assignment added to an already demanding holiday break period, leading to increased stress and reduced academic recovery time for some students. Moreover, the task was often completed merely as a duty and not enquiry, with students aiming to tick it off their to-do list rather than engage meaningfully with its content. As a result, the pre-field school assignment was eventually discontinued. This experience emphasised the importance of integrating field preparation within the formal academic schedule, rather than treating it as an add-on.

In place of the pre-field school assignment, we began to rely more heavily on field-based mini lectures. These sessions were delivered on-site, often using large geological maps or hand-drawn illustrations on portable whiteboard charts (Figure 2.4). They proved effective in introducing key geological concepts, reinforcing earlier learning, and supporting the development of spatial reasoning, an essential

but underdeveloped skill in most first-year students. Moreover, the informal nature of these lectures allowed the teaching staff to engage directly with emerging student questions and to adapt the content based on observed gaps in understanding. Formative feedback was provided through verbal questioning and notebook reviews on site, enabling responsive teaching aligned with the students' current Zone of Proximal Development (Vygotsky, 1978; Hedegaard, 2012). However, field-based lectures also came with notable logistical and pedagogical limitations. The open-air setting meant that distractions such as wind, heat, and ambient noise (including from a nearby training airport) frequently disrupted student attention. The physical arrangement of students in a loose circle or semi-circle made it difficult to ensure that all were equally engaged or even able to see the visual aids. Furthermore, the visual aids themselves were constrained by size and accessibility, as portable maps and diagrams are often too small compared to PowerPoint projections, and ad-hoc sketches on whiteboard charts are too rushed to be fully effective. Another challenge with the mini lectures is that they can sometimes run over the allocated time and reduce the amount of time available for students to make observations and notebook descriptions.

The introduction of polished hand specimens and photomicrograph charts into the field environment was one of the most successful and widely appreciated interventions. These tools provided immediate tactile and visual support for students grappling with lithological descriptions. By examining familiar polished samples alongside *in situ* outcrops, students were able to make clearer connections between laboratory-based skills and field observations. The photomicrographs, in particular, added a new layer of resolution to the interpretive process. Students could identify mineral boundaries, grain relationships, cementation patterns, and other microscale features that are typically inaccessible during standard fieldwork. Although some teaching staff initially questioned whether this reduced the emphasis on learning how to use a hand lens, the approach prioritises conceptual clarity and confidence-building before transitioning to more advanced interpretive tools, which is essential for the

first-year level. The strategy proved especially effective in supporting students who were still consolidating foundational knowledge and observational strategies.

The use of guided question sheets was another intervention designed to scaffold the learning process and ensure that all students systematically engaged with essential geological features. These sheets provided prompts for descriptive tasks (e.g., grain size, sorting, mineral identification) as well as interpretive questions (e.g., depositional environment, structural history). By gradually shifting the cognitive load from teaching staff to learner, this approach encouraged independence while maintaining focus on core learning objectives. Importantly, the question sheets helped to mitigate cognitive paralysis often experienced by students when faced with complex or unfamiliar outcrops. They acted as a checklist and a thinking scaffold, reducing ambiguity and ensuring a baseline level of descriptive completeness in notebooks. However, we also noted a trade-off: some students treated the questions as a rigid script rather than a guide. This led to formulaic thinking or premature interpretation based on expectation rather than evidence. In some cases, students made incorrect assumptions simply because they inferred that the question implied a particular answer. This highlights the importance of teaching students how to use guided tools critically, rather than mechanically.

The modular field exercises allowed students to focus on discrete, manageable activities. Feedback from students indicated that they appreciated the modular approach, which made expectations clearer and allowed for more focused engagement. The exercises encouraged methodical work and provided teaching staff with varied assessment artefacts. However, time management emerged as a consistent issue. Some students struggled to complete both the modular exercises and the required notebook descriptions and sketches, often prioritising one at the expense of the other. This led to inconsistencies that affected the overall marks of some students and highlighted the need to better synchronise workload expectations across the multiple assessment types.

# 7. Discussion

## 7.1. Lessons Learned and Emerging Insights

The pedagogical strategies that we employed were developed to scaffold learning and build disciplinary confidence (Van der Stuyf, 2002; Van de Pol *et al.,* 2010), but their effectiveness was mediated by a complex interplay of social, cognitive, and logistical factors. The challenges associated with teaching first-year geological field techniques in South Africa are compounded by systemic inequities in the country's education system. Many of our students come from under-resourced rural and township schools where Science education tends to be abstract, examination-oriented, and removed from practical or experiential learning. As a result, a significant portion of the cohort enters university with minimal exposure to natural settings from an epistemological perspective, minimal familiarity with scientific equipment, or little to no experience in field-based activities. Some students express discomfort in nature, unfamiliarity with outdoor learning environments, or fear of elements such as insects, which can directly affect their ability to engage meaningfully with fieldwork (Stokes & Boyle, 2009; Mogk & Goodwin, 2012; Giles *et al.,* 2020). Language diversity and academic preparedness further shape the learning opportunities. Geological fieldwork demands the use of technical vocabulary, inferential reasoning, and precision in description, skills that are challenging even in one's home language, and doubly so when students are engaging in a second or third language (Elkins & Elkins, 2007; Stokes & Boyle, 2009; Dolphin *et al.,* 2019; Chiarella & Vurro, 2020; Fonck, 2024). Our field school interventions, thus, had to operate with these realities in mind, offering scaffolding mechanisms that would support all students regardless of their starting point.

The success, or lack thereof in our case, of the pre-field school assignment reinforced the value of early engagement with the geological context (Butler, 2008; Dolphin *et al.,* 2019). When performed meaningfully, such preparation can reduce cognitive overload, build confidence, and promote the use of appropriate terminology. However, the long-term sustainability of this intervention faltered because of workload misalignment and the

absence of dedicated time within the academic timetable. This highlights the importance of ensuring that preparatory work is not only pedagogically sound but also practically manageable in consideration of the students' other academic obligations. Polished specimens and photomicrographs affirmed the pedagogical value of prioritising student understanding and confidence over strict adherence to traditional tools (e.g., hand lenses). A key lesson here is that accessibility precedes mastery: before students can apply professional tools independently, they need time and support to internalise what they are expected to see. The guided question sheets helped to provide a structured pathway for observation and interpretation, but their formulaic nature occasionally led to prescriptive thinking and unsupported assumptions when the question sheets were provided upon arrival at a locality. The lessons with using them is to blend scaffolding with open-ended tasks such as including metacognitive prompts (e.g., "What surprised you at this stop?") or open sketching time prior to using the guided sheets.

A structural challenge in the implementation of integrated field teaching is the timing and placement of the field school during the university recess period between semesters 1 and 2. Embedding the field school within the active academic semester is not possible in our case because first-year students in our programme are enrolled in a double major qualification and have other modules outside Geology. Further, the lack of scheduled contact hours for the field school significantly limits opportunities for progressive field preparation, student engagement, and scaffolding of core skills prior to the field experience (Butler, 2008). The field school's placement outside of regular teaching weeks also affects student motivation and continuity of learning. Field teaching is most effective when it builds progressively on classroom content, allowing students to transfer and test concepts in authentic, suitable settings (Butler, 2008; Mogk & Goodwin, 2012). The current structure disrupts this continuity, and for many students, especially those who are new to experiential learning, this results in a disconnect between theoretical knowledge and practical application. This

temporal gap might be contributing to the cognitive overload often observed during the early days of fieldwork, as students must rapidly reacquaint themselves with content that has not been actively reinforced. These challenges highlight the need for institutional reform in how field modules are timetabled and resourced (Butler, 2008).

## 7.2. Advancing Inclusive Field Pedagogy

One of the most pertinent outcomes from our study is that fieldwork pedagogy must be intentionally inclusive, especially in systems where students do not arrive with the same baseline of exposure, confidence, or cultural comfort in outdoor learning. Our efforts challenge a long-standing assumption in Geoscience education that all students must "sink or swim" in the field (Stokes & Boyle, 2009; Stokes *et al.*, 2011; Giles *et al.*, 2020). Instead, our work affirms that accessibility and inclusivity are not contradictory to academic rigour; rather, they are essential foundations for fostering deep, meaningful learning in field contexts. Moreover, our efforts point to the centrality of cognitive scaffolding in field-based SoTL (Van der Stuyf, 2002; Van de Pol *et al.,* 2010). Students cannot be expected to perform authentic disciplinary reasoning without carefully designed support systems that model, guide, and gradually assign responsibility, also noted by Butler (2008) and Stokes and Boyle (2009). It is important in our context that SoTL studies are conducted that investigate not just whether students "get it", but how they are helped to get it, and what interventions are most effective for diverse students across different epistemic stages (Butler, 2008; Elkins & Elkins, 2007; Mogk & Goodwin, 2012; Esteves *et al.,* 2013).

The transition from a monolithic notebook-based assessment to modular, task-based exercises promoted a shift in how learning is observed, measured, and supported. In SoTL, this raises important questions about assessment validity and authenticity in experiential settings. Modular assessments promote scaffolding by offering multiple opportunities to demonstrate learning, reducing cognitive load, and allowing for targeted feedback. This shift has led us to question how

assessment can be reimagined not just as a measure of content retention, but as an active tool for learning development. But more empirical work is needed to explore how multimodal assessment (visual, spatial, verbal, and written) can better capture student thinking in dynamic environments. In this context, the integration of technology holds considerable promise for advancing inclusive field pedagogy in place-based learning. Tools such as digital field guides and interactive geological maps or photomicrographs, and QR-linked audiovisual explanations can support differentiated learning by offering content in multiple modes and at varying levels of complexity. Such technologies enable real-time scaffolding for students who may be unfamiliar with field environments or working in a second language, while also promoting self-directed learning and collaboration (Dolphin *et al.,* 2019; Chiarella & Vurro, 2020; Giles *et al.,* 2020). When thoughtfully deployed, technology can help to diversify assessment formats and democratise access to field learning experiences, making geoscience education more responsive to the needs of diverse learners (Dolphin *et al.,* 2019; Chiarella & Vurro, 2020).

## 8. Conclusion

This chapter has explored the rationale behind the implementation of various pedagogical initiatives aimed at integrating formal and out-of-classroom curricula within a first-year geological field techniques module, and the critical evaluation thereof. Situated in a South African university context marked by student diversity, under-preparedness for tertiary education, and limited prior exposure to experiential science in the outdoors, our interventions were designed to create a more accessible and coherent transition from classroom-based theory to field-based practice. These interventions ranged from pre-field school assignments and site-specific lectures to the use of laboratory-informed field tools, guided observational prompts, and modular task-based assessments. They reflect a deliberate effort to scaffold student learning before, during, and after the field experience. The interventions not only supported

cognitive development and engagement but also addressed key pedagogical challenges, such as reducing novelty-related anxiety, encouraging observational accuracy and precision, and making field activities more meaningful and achievable for all students. At the same time, our reflections revealed several challenges and limitations related to the implementation of the interventions. The structural separation of the field school from the main teaching semester constrained preparatory engagement and complicated curriculum alignment. Some interventions, such as the pre-field school assignment, proved unsustainable in the long term because of institutional scheduling and workload pressures. Others, such as guided question sheets, highlighted the fine balance between providing structure and allowing space for independent enquiry. Still, the broader shift from monolithic, one-size-fits-all field practices towards more modular, inclusive, and context-responsive approaches marks a meaningful step forward in transforming how field techniques are taught at UJ. Amongst the interventions implemented, the most effective strategies were those that explicitly bridged laboratory-based learning with field observations, particularly through the use of polished hand specimens and photomicrograph charts that helped students to connect microscopic textures with outcrop-scale features. Guided question sheets and modular field exercises also proved valuable in scaffolding the observational process, enabling students to move progressively from basic description towards interpretation while reducing the paralysis often experienced in unfamiliar field environments. Together, these approaches created a more coherent integration of formal and informal learning by linking theoretical concepts, laboratory skills, and field-based enquiry into a structured yet flexible learning experience.

Importantly, this chapter contributes a Global South perspective to the Scholarship of Teaching and Learning in Geoscience. Beyond its immediate pedagogical implications, this study contributes to the Scholarship of Teaching and Learning by demonstrating how systematic reflective practice

can serve as a framework for iterative curriculum renewal in field-based education. Through the application of Schön's reflective practice, the chapter illustrates how teaching interventions can be critically evaluated in fieldwork learning environments and subsequently refined to better align formal disciplinary knowledge with experiential learning contexts. In doing so, the work advances evidence-informed field pedagogy and highlights the value of reflective teaching as a driver of curriculum innovation in Geoscience education. This chapter emphasises the value of pedagogical approaches that must consider cognitive and emotional aspects, while still guiding them towards deeper disciplinary engagement and educational growth. The integration of visual tools and differentiated tasks into field instruction offers promising pathways for making Geoscience education more inclusive, more effective, and more equitable. Looking ahead, we advocate for ongoing improvements in the more successful interventions, integration of field-based digital applications, empirical evaluation of the module grade and student feedback, and enhanced reflective practices in field pedagogy. There is a pressing need for more comparative research on multimodal and scaffolded learning in field settings, particularly in underrepresented educational contexts. Through sustained enquiry and collaborative innovation, Geoscience educators can continue to reimagine fieldwork not just as a rite of disciplinary passage, but as a transformative, inclusive, and intellectually generative space for all students.

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## Appendix A: Example of guided question sheet

**Locality 7: Questions to consider in the descriptions of your observations:**

1. **How would you describe the overall texture of the rock?**
   1.1. Is it consistently coarse, or do you notice areas of finer material?
   1.2. Are there both clasts and matrix? If there are clasts, are they rounded or angular?
   1.3. Is it clast-supported or matrix-supported?
   1.4. What are the clast sizes and grain size of the matrix?
   1.5. What are the compositions of the clasts and matrix?
   1.6. Is there any orientation or alignment of the clasts within the matrix? Or they appear randomly distributed?
2. **Are there layers within the rock, or does it appear massive and unstratified?**
3. **Can you identify any clasts that might have striations or grooves on their surfaces?**
4. **What depositional environments might produce a rock with such a mixture of grain sizes?**
5. **Given the size and composition of the clasts, can you infer anything about their source or transport history?**
6. **Why might some of the clasts have striations or grooves? What processes could cause these features?**

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Chapter 3

# A Self Reflection of Teaching Food Science and Technology at a South African University: The Incorporation of Daily Food Experiences to Enhance Learning

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## Abstract

Food Science and Technology disciplines are interwoven in the fabric of our society in that food, the subject matter forms part of our daily and societal lives. The world population is estimated to increase to 9.7 billion by the year 2050, with increasing imbalances in our food systems, it becomes increasingly important to train the next generation of food scientists and technologists. In the South African context of higher education and learning, Food Science and Technology are commonly mystified, believed to be courses associated with the home economics. This is also compounded by a myriad socioeconomic challenges that students face which hinders the learning processes. To this end, demystifying Food Science and Technology as disciplines of choice is vital in influencing the next generation of scientists who will contribute towards realising a resilient food system. In this chapter, I give a narrative reflection of teaching Food Biochemistry and Food Technology modules to undergraduate

students at the University of Johannesburg, the aim of which is to examine the efficiency of my teaching practice and instructional decisions on the students' engagement. In addition, I noticed that during class engagements, some students were more enthusiastic than others; which, in turn, prompted me to study how the incorporation of daily food experiences to explain chemistry and technology-related principles improves students' understanding. Furthermore, emphasis indicating the importance of utilising various teaching methods and theories such as constructivism theory, collaborative learning, active learning, and gamification are highlighted. Collectively, these approaches have enabled a respective module success rate of above 75% since 2020. Finally, as part of the reflective process, the engagement with students' lecturer and module evaluation reports has demonstrated a need for additional weekly tutorials and quicker feedback on practical reports, addressing this with added slots for consultation and timeous feedback has shown improved student performance and satisfaction.

**Keywords:** Active learning, Constructivism, Food Biochemistry, Food Science and Technology, Gamification, Kahoot

## 1. Introduction: Food Science and Technology

The teaching of Food Science and Food Technology presents a unique opportunity to reflect on how students come to understand a discipline that is both scientifically rigorous and socially indispensable. Food Science, defined as the study of the physical, biological and chemical composition of food alongside the principles of food processing and preservation (IFT, 2019), plays a critical role in shaping safe, sustainable, and nutritious food systems. Food Technology further extends this role by focusing on the processing, packaging and distribution of food to meet the needs of diverse populations. Nevertheless, the South African food system faces escalating challenges including rising food insecurity, lack of dietary diversity, child stunting caused by malnutrition, foodborne illnesses, increasing food waste, and a growing obesity epidemic (Ronquest-Ross & Sigge, 2024) which demand a re-examination of how these subjects are taught in higher education. As an educator, these conditions

compel me to reflect on whether my teaching practices effectively prepare students to address such societal concerns and whether my curriculum meaningfully connects scientific knowledge to real-world food system issues.

A reflective challenge emerges from the reality that many students enter Food Science and Technology programmes with limited awareness or misconceptions about the field. Research indicates that these disciplines are rarely students' first or even second choices at university, and are often mistakenly associated with home economics, cooking, or hospitality-related professions (Jideani *et al.*, 2013; Sigge, 2023). These misconceptions influence student motivation, classroom engagement, and the development of a strong disciplinary identity. Through a Scholarship of Teaching and Learning (SoTL) perspective, such misunderstandings are not simply student deficits but become valuable indicators for enquiry. They signal the need to investigate how students perceive the discipline, how they make meaning during learning, and how teaching practices can be adapted to bridge gaps between expectations and disciplinary realities. Thus, reflection becomes a scholarly act, an intentional, evidence-informed process of questioning one's assumptions, gathering data on student experiences, and refining pedagogical strategies to deepen learning.

This reflection is especially important considering the global urgency surrounding food production systems. With the world population projected to reach 9.7 billion by 2050 (United Nations, 2019), there is an increasing demand for graduates capable of contributing to innovative, sustainable and equitable food systems, necessitating a reformed or decolonised curriculum that aligns with the South African higher education national curriculum priorities. As an educator, I have a responsibility not only to teach disciplinary content but also to cultivate students' sense of purpose and societal relevance in addressing food security challenges. To this end, effective teaching in Food Science and Technology, therefore, extends beyond laboratory skills and theoretical knowledge; it involves shaping students' understanding of their future role in achieving broader

developmental priorities, including Sustainable Development Goals 1 (No Poverty) and 2 (Zero Hunger). Framing my practice within a SoTL approach encourages me to reflect systematically on how my teaching can empower students to become agents of change within the food system. This introduction, thus, sets the stage for a reflective enquiry into how I teach, how students learn, and how both processes can evolve to better serve the demands of our changing world.

## 2. My role as a Lecturer

As a lecturer, I have worked with many students whose diverse environmental, societal, cultural, and religious backgrounds shape the way in which they learn. These presuppositions influence their engagement, understanding, and overall learning experience. Therefore, my responsibility as a lecturer is to identify and, where possible, remove any barriers that may hinder learning at all levels, ensuring that every student has an equitable opportunity to succeed. This is achieved by affirming to students that they are capable of great achievements despite the societal, economic, and environmental challenges that they may face. In other words, I intentionally communicate my belief in their ability to learn and succeed, recognising that my perception of them can significantly influence their learning process. This approach aligns with the pedagogy of care. Larsen (2015) articulates this powerfully: "*When students are asked about their motivation to succeed in a course, about whether they enjoyed their instructor, and about their overall satisfaction with the class, answers can often be traced back to an educator who was perceived by the student as caring.*" Below is a comment excerpted (Figure 3.1) from a teaching and learning evaluation report, which encapsulates this commitment to fostering a supportive and caring learning environment.

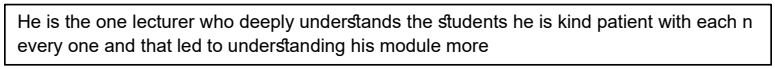



**Figure 3.1:** An excerpt from a teaching evaluation demonstrating care.

I regard teaching as an intellectual partnership in which understanding is constructed rather than transmitted, and where learning is as much about personal transformation as it is about mastery of content. My approach, therefore, draws on three interrelated theoretical perspectives: Transformative Learning, which cultivates critical reflection and self-awareness; Constructivism, which situates knowledge within social and cultural interaction; and Experiential Learning, which anchors understanding in authentic practice. Together, these theories provide a coherent framework for developing reflective, capable, and ethically minded graduates who can translate classroom knowledge into meaningful societal contribution.

The first underlying theory that guides my practice is the theory of transformative learning, as outlined by Mezirow (1997). Transformative learning centres around the need for students to critically reflect on their assumptions that are shaped by social, cultural, and historical contexts. I have discovered that Food Technology students usually come with preconceptions regarding its so-called "low status" compared to other sciences. I counter these assumptions by integrating reflective exercises within my modules that link course material to societal problems like food insecurity, food justice, and sustainable consumption. For example, while learning about lipid oxidation, students are encouraged to reflect on how food security in rural communities without refrigeration is impacted by oxidative change in food. These scenarios make them critically re-examine their understanding of food science as a tool for public health and sustainable development. Brookfield (2000) also posits that critical reflection not only empowers but also builds democratic competencies, making them ready for active citizenship. I also use writing prompts and class discussions with guidance to challenge the ethics issues in biotechnology, food wastage, and industrial food manufacturing. This critical dialogue essential to transformative pedagogy fosters intellectual receptivity, cultural understanding, and civic engagement (Mezirow, 1997). With the questioning to identify biochemical reactions with community effects, they begin to envision themselves as social change-makers, which also addresses my value of transformative potential. In addition, the affective richness established in this reflective exercise immediately addresses humanistic values, especially the focus on

self-actualisation. Cranton (2016) points out that change is not strictly cognitive but is also affective and spiritual in nature, which I experience when students express new agency within learning. My teacher feedback is intentionally conversational and serves the goal of facilitating students through cognitive dissonance, a gateway to change. My use of humour in the classroom is not accidental but intentional, heeding the call of the intentional, appropriate use of humour to improve learning outcomes. Humour, as noted by Garner (2006), can become a mental and emotional spur, which enhances recollection and facilitates an inclusive learning environment. In Food Biochemistry, I have a habit of using earthy analogies and with examples, such as comparing enzymatic browning to a banana's "bad mood" to reveal complex reactions. In another lesson, where focus was about the importance of gluten (a protein found in flour) in baking, I remember saying "*gluten is so important, that you can liken it to bungy jumping strings, if you don't have gluten in baking it's the same as going to bungy jumping with no strings attached*". This approach minimises learner anxiety and encourages engagement. Humour also complements my humanistic bias in creating a psychically safe environment where learners experience respect and are valued (Rogers, 1983). Used deliberately, it can help to create collaborative learning, cultural bonding, and even critical thinking, particularly to demolish assumptions regarding transformative dialogues. Thus, humour becomes a tool greater than entertainment; it becomes a pedagogical device based on theory and in congruence with my values of empathy, humility, and change. As a teacher, this has allowed me to recognise dramatic differences in student motivation and engagement. Students no longer study to pass but to be able to contribute to solutions practically, which addresses the compatibility of my philosophy and transformative learning. Taylor (2009) explains that to facilitate transformative learning, not only good content is needed, but also a lecturer's ability to deal with the emotional nuances of students as they undertake this journey. While transformative learning reshapes personal perspectives, constructivism provides the cognitive scaffolding for that transformation. It shifts the focus from what students learn to how they construct meaning, positioning the learner as an active participant in the creation of knowledge rather than a passive recipient.

Constructivist theory of learning enhances my pedagogy by asserting that students actively construct knowledge from their prior experiences and environmental realities (Piaget, 1972; Vygotsky, 1978). My conviction that students do not acquire knowledge passively but interpret it actively finds voice in this theory. In my classroom, I use common food and cultural practices to explain complex biochemical events. For example, the explanation of protein denaturation comes from the texture change of the meat in traditional stewing processes. This encourages the students to relate new information to previous knowledge, improving retention and understanding. My use of group projects and peer discussion draws from Vygotsky's social constructivism, where interactivity in learning is emphasised. Examples of these are peer-led tutorials, scenario problem-solving, and group review writing. Bransford *et al.,* (1999) assert that learning environments need to be able to facilitate social negotiation of meaning, which I practice through structuring varied groupings that reflect workplace heterogeneity. These practices reflect my empathy and inclusivity principles by guaranteeing that all voices are heard and learning is socially situated. My humility value is actualised through mutual learning: I freely admit my own ignorance and encourage students to challenge ideas, fostering an environment of respect for each other. I recall an incident where I was making an example with a food product in a Food Biochemistry class, one of the students raised a hand and called me to correction, I conceded and went back to retail stores to further investigate. In our subsequent class I declared my mistake and class engagement from that point on was outstanding, as many of the students had confidence and respect in me because of the admission that I also make mistakes. Inclusivity is no longer a buzzword; it is a methodology, as I strive to see all the material, from biochemical pathways to food production, presented in culturally appropriate language, such as biochemical illustration of starch gelatinisation in traditional pap preparation. These tactics reflect directly the humanistic focus on student agency, emotional well-being, and overall growth. Above all, my aim is not just to educate subject matter but to motivate students' growth, purpose, and resiliency. This supports research by McCombs and Whisler (1997), who encourage learner-centred

psychological principles to construct equal classroom experiences. Above all, constructivism allows me to appreciate student diversity both in demographic situations but also in epistemological styles, some are visual learners, some are kinaesthetic, and some are linguistic. My instructional materials, therefore, include visual aids, laboratory demonstrations, discussion prompts, and reflection journals. Constructivism, therefore, not only guides my teaching strategy, it allows me to put into practice my assumptions regarding individualised, respectful, and student-focused learning. The theory also endorses my commitment to humility as I learn from student feedback, which continually redefines my own understanding of content and pedagogy. Schunk and Mullen (2012) contributes that deep learning is dependent on the integration of prior knowledge and engagement, principles that motivate my everyday teaching interactions. Constructivism finds its most tangible expression in experiential learning, where theory meets practice. By translating abstract understanding into concrete action, experiential learning completes the cycle of reflection and engagement, allowing students to test, refine, and internalise their knowledge through lived experience.

The third aspect of my teaching style is that of experiential learning from the work of Kolb (1984). It follows the belief that learning is the construction of knowledge by experience and not by the receipt of instructions. The type of learning also assumes that the students commence from a usable background experience that will be refined by reflection, by doing things, and by reapplication.

Embedded in this theory are central educational values of reflection, authenticity, empowerment, and adaptability. Reflection enables students to derive meaning from experience; authenticity keeps the learning relevant to the concrete contexts of everyday life; empowerment heightens the students' sense of ownership for their learning; and adaptability instils in them the mindset that mistakes are a means of growth. These values together bring the otherwise abstract notion of experience education a human touch and a fluid quality that fosters the building of competence and confidence.

Experiential learning, as defined by Kolb (1984) and later developed by Beard and Wilson (2018), has continued to be the third pillar of my personal teaching practice. It is built upon the

principle that learning takes place through the conversion of experience rather than the receipt of information by the passive absorber. Every learner brings their individual prior experience, intuition, and cultural understanding into the classroom, which may be rich soil for building new understanding. If these experiences are deliberately brought into focused patterns of structured action and reflection, they foster intellectual and personal growth so that students are able to connect theory to real, experienced contexts (Illeris, 2018).

Reflection that translates experience into insight lies at the heart of experiential learning. Reflection causes the learner to pause, review, and reinterpret their activity in the light of theory's principles. After Food Biochemistry 3 laboratory exercises, I ask students for their experimental outcomes, but also their decisions and the justification that guided them. This directed reflection warrants metacognitive awareness and critical questioning; the genesis of lifelong learning (Boud *et al.*, 2013; Schön, 1995). It also aligns itself with Dewey's (1938) postulation that reflection gives continuity and direction to experience and transforms activity into education.

Complementary to the aspect of reflection is the element of authenticity that makes the learning pertinent and usable to the context. I create class and laboratory exercises analogous to real-world scenarios of food technology, at the level of condiment shelf-stable formulation or loss reduction after harvest. Motivation is highest when the students see the work's applicability to the world, and they themselves see the scientific base of knowledge itself as a tool for community well-being. This focus on authentic engagement is in alignment with recent research that demonstrates context-rich learning environments enabling conceptual retention building and professional identity construction (Lombardi *et al.*, 2021; Herrington & Oliver, 2000).

Empowerment is a further defining characteristic that derives its roots in the belief that students are themselves agents of their learning experience. Empowerment is when students are able to generate aspects of their experiments themselves, negotiate the assessment criteria themselves, or take charge of peer-teaching activities. Such activities encourage confidence and intrinsic motivation, again repeating the argument of Kolb

(1984) that rich experience breeds self-direction and adaptive expertise. Empowerment also finds itself nicely in accordance with constructivist ideology by rendering the learner the joint co-creator of knowledge itself rather than the receiver.

Also, the element of flexibility is key, which reflects the unpredictable and fluid nature of science and learning itself. Should experiments fail or yield counterintuitive results, I have students interpret the why and revisit their hypotheses. This flexible mode of thinking engenders resilience and intellectual humbleness, abilities imperative for scientists in this day and age where technologies are transforming quickly and worldwide needs are connected to nourishing the population (Fenwick, 2001). Framing uncertainty as a fertile area for exploration turns frustration into curiosity and failure into learning. Together, these related values of reflection, authenticity, empowerment, and flexibility create a whole-person model that transforms procedural experience of learning into a developmental and reflective process. Repeated cycles of concrete experience, reflective observation, abstract conceptualisation, and active experimentation (Kolb, 1984) see my module students learn to master technique but also interpret, question, and innovate responsibly. This blend of belief, value, and practice indicates my commitment to preparing graduates competent but also self-aware and able to significantly add to their profession and society.

## 3. My Teaching Practice

Presently, I teach: Food Biochemistry 3 (FTNBC2A) and Food Technology 4 (FTN7X05). They are advanced modules that integrate theory and practice. Informed by humanistic learning theory, I establish each term with a setting of caring and inclusion. Prior to the commencement of formal teaching, I establish students' expectations, backgrounds, and personal aims through short questionnaires and informal consultation. This tradition based on empathy and modesty enables me to establish a psychologically safe learning environment where students experience buoyancy and respect (Rogers, 1983; Noddings, 2003).

Although technology has a significant part to play in contemporary teaching, I have found that some students become nervous where learning too heavily involves the use of digital technology. By keeping the balance, I continue to make very frequent use of the chalkboard and document camera in teaching. My presentation slides are presented on Moodle so that students have access to them to review material at their own pace. In supplementing understanding, in areas related to chemistry in particular, I point students to selected videos on YouTube. I prefer those by Prof Barry Bowman of the University of California, Santa Cruz, because these have clear and tempoed explanations that enhance understanding. By having both these videos and presentation slides available before each class, students have the opportunity to come with background knowledge. This then gives me an opportunity to begin each session with questions that relate new material to existing knowledge on the part of the students, in accordance with constructivist learning. Although not all students come with advance knowledge, this approach typically promotes curiosity and participation in subsequent sessions.

In Food Biochemistry 3, I apply transformative learning principles through relating scientific theory to real-world issues. In the teaching of processes such as lipid oxidation or protein denaturation, I ask students to contemplate how these biochemical processes apply to South African food systems, particularly preservation and food security. Students also keep reflective journals so that they can return to earlier assumptions and ponder how community nutrition might apply to biochemistry. These pedagogies promote reflective thinking and connect scientific and social understanding and guidance of transformation and respect of lived experience (Mezirow, 1997; Cranton, 2016).

Constructivist learning is facilitated with scenario learning and groupwork. In Food Technology 4, for example, students carry out scenario-based traditional food production such as *mahewu* or *achaar* and need to consider microbial safety and processing design. Groupwork promotes peer learning and discussion where peer review also helps students to develop reflective and analytical ability. Such groupwork makes learning purposeful and meaningful to students' contexts and not abstract and disconnected from practical life (Vygotsky, 1978).

To link both classroom and online learning, I utilise Moodle to make announcements, submit assignments, and take short quizzes. This merging of both types of learning ensures that in-class and online learning both culminate in the same results. I utilise questioning in class to promote discussion and critical thinking and have students view themselves as participators and not just auditors.

Experiential learning sits at the centre of how I teach, especially in the laboratory where students learn best by doing. I see it as more than a method; it is a way of guiding students to think like scientists through their own experience. In my classes, I want them to test, question, make mistakes, and discover how theory connects with the real world of food science.

In Food Biochemistry 3, I run weekly practicals where students work with real examples rather than just notes from the slides. They test things like enzyme activity, look at antioxidant levels in foods, and check how heat or pH changes the texture or colour of food samples. Before we begin, I ask them what they think might happen and why, and the conversation often sets the tone for the session. Afterwards, we sit together to look at what actually happened. Sometimes results are what they expected, sometimes not at all, and that's where the real learning starts.

Students talk about the differences that they noticed, why one group obtained better readings than another, and what they think caused the variation. I usually ask students to write a few sentences about what they saw in the laboratory and how it links to what we covered in the lecture. When we meet again, I take out what they wrote, and we read through a few of the reflections together. I ask them to point out what made sense to them and what didn't. Some share what worked well in their groups, while others talk about what confused them or what they might do differently if they had another chance. The conversation usually opens up from there, and it's clear that they're beginning to connect the lab work with the theory in a more personal way. The discussion often moves in unexpected directions, and that's usually when the best learning happens. Those sessions are often noisy and full of energy. Some students laugh about things that went wrong, others point out what worked for them, and now and then someone brings up an idea that none of us had thought about before. It's one of the best

parts of the module because you can actually see them thinking through their own learning. The aim is to help them to realise that science isn't about perfect numbers; it's about reasoning through the process and understanding why something worked or didn't.

In Food Technology 4, the learning takes on a more professional angle. Students work on projects that resemble real industry challenges. They design, test, and improve food products, analysing issues such as stability, texture, flavour, and shelf life. Some projects grow from their own work experiences or community food practices. This approach brings science to life and shows them how their classroom knowledge can solve real problems in the South African food sector. I find that students become more confident when they realise that the work that they perform in class mirrors what professionals do outside of it.

Each year, my Food Biochemistry 3 students also take part in the South African Association for Food Science & Technology (SAAFoST) student product development competition. Each year, my students present the products that they have developed in the module to a panel of food scientists and industry guests at the SAAFoST competition. Preparing for this event takes a lot of effort. They spend several days refining their formulations, checking the quality of their products, and practicing how to explain their ideas to professionals. It is demanding work, but also an exciting process, and for many it becomes the moment when they realise how much they have grown. Standing in front of experienced food scientists gives them a kind of confidence that a lecture alone could never achieve.

The contest brings a mix of nerves and pride. Some students are nervous about judges' questions; others can't wait to present their creations. And by day's end, they stroll away feeling accomplished and more confident in what they can do. One of the best parts of being a lecturer is watching them present their work and respond thoughtfully to feedback. It makes classroom lessons concrete and starts to encourage students to see themselves as future food professionals. It forces the students to collaborate, ration their time, and explain their ideas to people outside the classroom. I've noticed that they often learn more from preparing for that event than from any single lecture, because they have to depend on each other and think on their feet.

Not every experiment goes the way that we hope. There are days when a reaction refuses to work or the numbers on the page make no sense at all. When that happens, I do not see it as a setback. We talk about it as part of learning. I ask the students to walk me through what they did from start to finish, and they often notice small things which they missed before. Sometimes the discussion takes longer than the experiment itself, but that is where the real learning takes place. By the end, most of them realise that mistakes are normal in science and that they often teach more than the perfect results ever could. It helps them to see that mistakes are normal in science and that what matters most is how they respond to them. The habit of analysing setbacks builds resilience, patience, and analytical thinking, all qualities needed in both research and industry.

Because food science is a collaborative field, I design practicals that require teamwork. Students rotate roles such as leader, recorder, and presenter, so everyone contributes. This practice encourages communication and accountability and exposes students to diverse ways of thinking. It also creates a sense of shared achievement when the group reaches a conclusion together. Throughout the semester, I provide feedback that goes beyond marking. When I give feedback, I try to talk about both the technical work and the way in which students reflect on what they learned. We look at their data, but also at how they explain their thinking and what they took from the task. These short conversations happen often, and over time the students begin to notice how much they have improved. They start to see learning as something that keeps developing rather than something that ends with a mark.

Assessment procedures of mine adhere to Bloom's Taxonomy (Anderson & Krathwohl, 2001) and advance from simple recall to advanced skills. Quizzes in the early weeks verify foundational knowledge, mid-semester projects cultivate application and analysis, and end-of-course tasks gauge creativity and synthesis. Ongoing feedback in the form of annotated rubrics, consultation, and collaborative debate promotes reflection and development. This procedure also adheres to my philosophy of a pedagogy of care (Larsen, 2015) that supports both scholarly and personal growth. For instance, early quizzes and recall exercises ensure students' recollections of biochemical terminology and basic concepts (Figure 3.2).

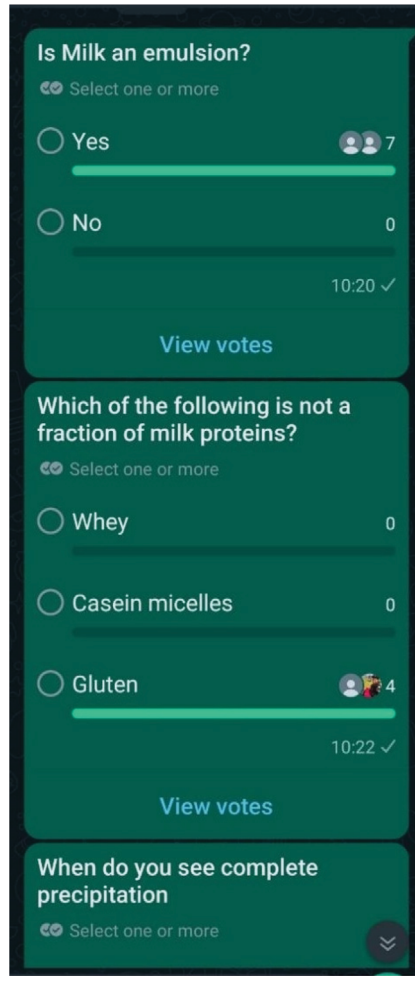



**Figure 3.2:** WhatsApp Quiz on Food Proteins (Food Biochemistry 3)

This approach enabled me to facilitate deeper discussions in subsequent lessons and reinforce students' understanding of key concepts particularly by analysing their answer choices and the volume of responses received. Demystifying Food Science and Technology, while creating a conducive learning environment for culturally, economically, and socially diverse groups of students, requires the intentional use of pedagogical tools that connect students' real-life experiences to the concepts being taught. Such tools help to immerse them in the learning process and

enhance their engagement with the content. To achieve this in my teaching, I draw on constructivist theory, which, according to McLeod (2023), asserts that learners actively construct their own knowledge and that reality is shaped by their lived experiences. Constructivism provides a framework that acknowledges learners' backgrounds, promotes meaning-making, and supports the integration of new information with existing cognitive structures. The specific constructivist approaches that guide my teaching practice include cognitive constructivism, collaborative learning, and active learning. Each of these contributes uniquely to fostering deep learning and student engagement, and they are discussed in detail in the subsequent sections.

### 3.1. Cognitive Constructivism

Drawing on McLeod's (2023) definition of cognitive constructivism which posits that knowledge is actively constructed by students based on their existing cognitive structures, making their understanding a reflection of their cognitive developmental stage, it becomes essential to recognise how each student's background and diversity influence their cognitive levels. In my Food Biochemistry and Food Technology classes, this diversity manifests in many ways. However, food, a universal element that connects people, serves as a fundamental tool through which I build on students' prior knowledge of food chemical reactions and food processing.

The Graduate Student Instructor (GSI) Teaching and Resource Center (2015) emphasises that cognitive teaching methods assist students in linking new information to prior knowledge, enabling them to adjust and expand their intellectual frameworks. In line with this approach, I often use relatable, everyday examples to scaffold learning. A pertinent illustration is the preparation of "pap," or stiff porridge, which I use to explain the concepts of starch gelatinisation in Food Biochemistry and fundamental food processing principles in Food Technology. This example not only grounds abstract biochemical processes in lived experience but also supports cognitive development by helping students to integrate new knowledge with familiar practices.

To further strengthen learning, I encourage active participation by posing probing questions that elicit student feedback on the learning outcomes and communication to the instructor. For instance, in the Advanced Diploma module, Food Technology 4 (FTN7X05), I frequently ask students to share industry experiences related to food processing technologies or equipment that they have used. Given that this module focuses on industrial-scale processing and preservation technologies, such exchanges allow the entire class to gain vicarious insight into the functioning of large-scale food industry equipment. These shared experiences form a foundational constructivist platform upon which I can extend and deepen their understanding.

However, given that UJ students come from varied educational, cultural, and socio-economic backgrounds, their learning needs and cognitive development stages differ significantly. For students who struggle to grasp concepts through primary cognitive constructivist methods, I incorporate additional approaches such as collaborative learning and active learning strategies. These methods ensure that all students, regardless of background, are supported through alternative pathways to understanding and are able to engage meaningfully with the course content.

## 3.2. Collaborative Learning

Teamwork is commonly used because of the world's rising desire to think strategically and collaborate jointly on pressing issues; hence, the focus has switched beyond solo endeavours to collective efforts (Laal *et al.,* 2013). Collaborative learning is a substantial departure from the traditional teacher-centred or lecture-centred method in the classroom, where participants work together while labouring towards similar objectives or achieving objectives. It contributes to the construction of understanding in daily settings through reciprocal engagement and support (Majid & Chitra, 2013) and shows how respectful relationships amongst individuals are maintained. It also emphasises individuals' collective strengths and triumphs, as well as their duties and regard for individuals' opinions. Cooperative learning centres on participants providing unanimous assent to reach a consensus (Laal *et al.,* 2013).

According to collaborative constructivism theory, learning is a social activity; it is something we do together rather than individually (Dewey, 1938). This is based on the belief that each student will have a distinct point of view about a particular subject based on existing knowledge and set values. This theory is very useful in group discussions, In Food Biochemistry 3, I had asked students to brainstorm how they would prevent enzymatic browning of fresh produce (a phenomenon the happens when fruits and vegetables turn brown when cut). Considering that students have different personalities, strength, and weaknesses, groups are strategically chosen so that "outspoken, quiet, reserved, strong, or weak" students complement each other.

The significance of collaborative learning in the Food Technology course could not be over-emphasised. This is because of the fact that after the completion of their qualifications, food technology professionals work with diverse groups of people from other professions including engineering, health, and regulatory agencies. Therefore, inculcating the ability of working collaboratively with others at the classroom level is very important. Food Biochemistry 3 caters for senior undergraduate students who are at the verge of branching into Advanced Diploma, Honours (which is a programme that started in January 2024), and higher postgraduate degrees. The notion of experiential learning emphasises the capacity for problem-solving and logical reasoning (Dewey, 1986). This significant learning experience is described as knowledge developed by sharing experiences or learning by doing (Konak *et al.*, 2014). Practical learning is a crucial process that allows students to actively participate in the acquisition of skills and information (Honey & Mumford, 1986). It refers to the learners' first-hand experiences creating a significance process in the absence of an instructor (Shiralkar, 2016). Students participate in experiential learning through activities, which is followed by the acquisition of information and skills, as well as the enhancement of their worth through best practice (Kang & Chen, 2016).

This sort of experiential learning is linked to the process of knowledge acquisition and refers to how pupils are motivated

and viewed, as well as the real experience which they gain through practical tasks. It is complicated and involves introspective judgements and how individuals reflect on what they have done or encountered, remembering, and information, direction, and counsel from specialists. Students benefit from observational learning and knowledge applications (Dewey, 1986). Students who engage in a systematic and ongoing experiential learning method can receive and apply information through real learning experiences. The learning experience of students is generated from the knowledge creation process through reflection on the work that they undertake, while acquiring knowledge entails learning with comprehension.

To this end, my last assessment before the semester ends usually includes a group project about the writing of a review paper. This assessment is aimed at sparking collaborative teamwork, communication, time and project management, and planning skills of students while at the same time inculcating their research abilities including the use of bibliometric searches, scientific writing, scientific arguments, and use of proper citations. Groups are typically asked to write about topics we had covered during the semester including, but not limited, to carbohydrates and food systems, polysaccharides, lipids, proteins, colours, and flavours.

## 3.3. Active Learning

As opposed to transmission-based learning, which perceives students as empty vessels ready to receive knowledge, active learning asserts that learners construct meaning only through active engagement with the world, such as experiments or live problem-solving (McLeod, 2023). Practices encouraging active learning emphasise skills development rather than information transmission and urge students to perform something that demands higher-order thinking (read, discuss, write). They also focus on students' investigations of their beliefs and ideals. Individuals learn by linking novel concepts and emotions to current knowledge and experiences to produce novel or improved comprehension, according to constructivist learning theory

(Bransford *et al.,* 1999). Piaget and colleagues proposed the idea that learners can either incorporate new knowledge into a current structure or adapt the existing structure to incorporate novel knowledge that opposes earlier thinking. Active learning approaches frequently explicitly urge students to establish linkages between new material and their present mental models, so expanding their comprehension. In other circumstances, teachers may develop learning activities that allow students to challenge misunderstandings, allowing them to rebuild their mental models on more correct understanding. In either case, techniques that encourage active learning foster the type of cognitive labour recognised by constructivist learning theory as important for learning. Active learning techniques frequently include the use of cooperative learning groups, a constructivist-based practice that emphasises the value of social interaction. Lev Vygotsky's work clarified the connection between thinking and interpersonal interactions, resulting in the sociocultural theory of growth, which proposes that learning occurs when learners solve problems that are above their present growth stage with the assistance of their instructor or peers (Vygotsky, 1978). Thus, group-based active learning techniques rely on this sociocultural branch of constructivist learning theory, utilising peer-peer cooperation to support students' construction of expanded and accurate mental models.

Another facet, typically used in active learning is the gamification of concept. Gamification is the application of game principles, mechanics, and elements in non-game environments (Christopoulos & Mystakidis, 2023). It utilises the fun features seen in games such as the completion of challenges, badge collection, leaderboards, and points collection, adding them into teaching and learning activities. This concept of learning has been incorporated as a diagnostic tool in Food Biochemistry and Food Technology modules. Students are given Kahoot quizzes (Figure 3.3) before, during, and after class, rewards are given to the top three students and runners-up on the leader board of the quiz. From the experience of the students, the Kahoots have been well received (excerpt below), promoting active learning.

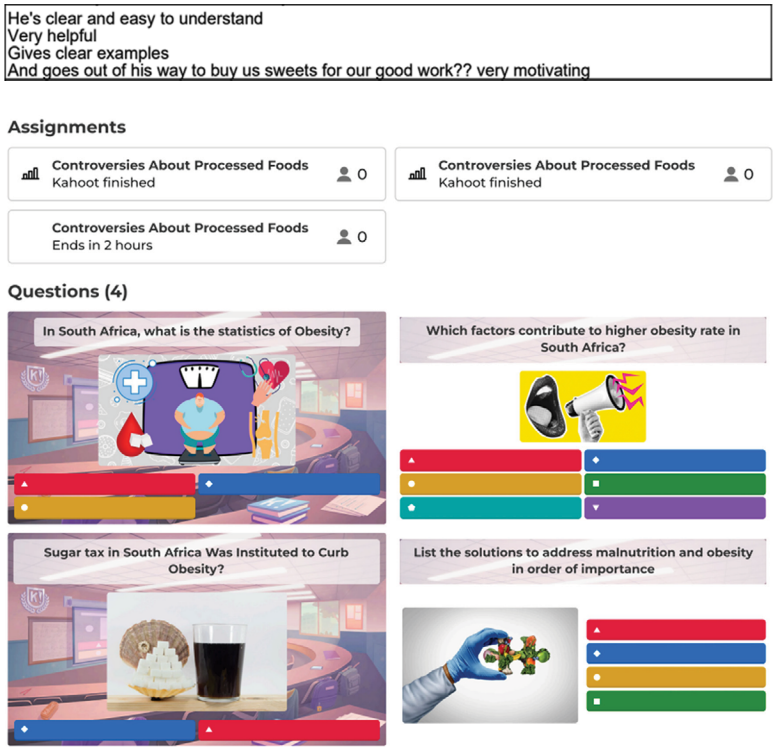



**Figure 3.3:** Kahoot based on controversies about processed food in Food Technology 4 module.

Finally, apart from using daily food experience in Food Biochemistry, students also have an opportunity to engage with the module through practical experimentation. Practical sessions are on a weekly basis, covering some of the core concepts in food chemistry. Students get to be trained to use analytical equipment which is important in food analysis as well as putting theory into practice when they investigate the effects of processing on the chemical properties of food. Thankfully, the Advanced Diploma students in Food Technology 4, gained industry experience a year prior, working in different sectors of Food Science and Technology.

## 4. Module Success

Through the incorporation of a blended teaching approach and the use of various teaching pedagogies, the success pass rate of the modules has remained above 75% over the last four years, as illustrated in Table 3.1.

**Table 3.1:** Module success rate from 2020 to 2024

| Year | Module name | Module code | Registered Students | Module success rate (%) |
|---|---|---|---|---|
| 2020 | Food Biochemistry | FTNBCA2 | 43 | 100 |
| 2021 | | | 78 | 100 |
| 2022 | | | 66 | 100 |
| 2023 | | | 59 | 100 |
| 2024 | | | 30 | 96 |
| 2020 | Food Technology 4 | FTN7X05 | 12 | 83 |
| 2021 | | | 23 | 100 |
| 2022 | | | 18 | 79 |
| 2023 | | | 23 | 75 |
| 2024 | | | 25 | 100 |

## 5. Conclusion

Working with student young adults is amazing and always necessitates continual evaluation to check if one is on track as far as the impartation of knowledge is concerned. Although at times there's a dichotomy between what I believe is essential for learning, some students may not necessarily believe so. Some areas of improvement are to provide more weekly tutorials and improve on timeous feedback when it comes to practical reports. Similarly, students have indicated at times that they struggle with the use of some of the English words used during lectures. This is

compounded by the jargon typically used in Food Biochemistry and Food Technology; however, to overcome this challenge, I have frequently asked students to express the words in native languages after I have simplified the Biochemistry and Food Technology terms. This is a collaborative effort between the lecturer and students and is to devise a form of "concordance" for typically used terminologies in these modules and have them included in learner and practical guides in the future. Finally, it is a privilege to influence minds of the next generation of impactful people in society; however, to be efficient in this requires continuous improvement and lifelong learning as social, economic, environmental and world dynamics are forever changing. This calls for me to think out of the box and constantly change certain paradigms.

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# Chapter 4

# Digital Tools for Effective Teaching of Chemistry

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## Abstract

Chemistry is a central science that supports several degrees and diplomas in the fields of Science, Health Sciences, Engineering, and Technology. However, many students who do not have a strong scientific background are often faced with the challenge of having to grasp key concepts that often appear as abstract concepts to them. Moreover, many students struggle with basic calculations, while others can perform calculations but simply cannot study theory or formulate answers to descriptive Chemistry questions. This chapter, therefore, explores the use of digital tools for the facilitation of the learning of Chemistry. It evaluates the role played by digital technologies in helping students who lack a scientific background to visualise and learn key concepts. It further evaluates the ability of digital tools to help students to learn descriptive chemistry more easily. The role played by AI tools such as ChatGPT in helping students to formulate answers to descriptive Chemistry questions is also highlighted. Lastly, the overall impact of digital tools in making the learning of Chemistry more enjoyable and in shifting from mundane notebook and textbook learning is critically discussed.

**Keywords:** Chemistry; digital tools; key concepts; scientific background; visualisation

## 1. Introduction

Chemistry is often perceived as a difficult subject to understand because of all the complex terminology and concepts that need to be grasped by students. On the other hand, it is considered to be a central scientific subject for many students undertaking studies in Science, Health Sciences, and Engineering faculties. As a result, many students are forced to take Chemistry as a pre-requisite subject even though this may not be their preferred subject. Very often, students tend to avoid Chemistry as a subject in high school but enrol in programmes at universities that require them to take Chemistry as a prerequisite subject. Consequently, such students are faced with the challenge of having to learn Chemistry from scratch, as a sound background in the subject is seriously lacking. This may, in turn, impact their progression towards subsequent years of study and timeous completion of their qualifications.

Additionally, some students also face challenges of having to suddenly learn Chemistry in English after having learnt the subject content in another language at high school. Moreover, some students are exceptionally good at performing basic Chemistry calculations but are unable to learn Descriptive Chemistry and, as a result, struggle to answer questions particularly based on theoretical concepts. There is a very prevalent negative mindset amongst students, especially when it comes to learning Organic Chemistry.

Besides the onset of the coronavirus disease 2019 (COVID-19) pandemic in 2020 (Villasmil, 2024), all the above challenges have also led to the need for the implementation of digital technologies in facilitating the teaching and learning of chemistry. This chapter, therefore, reviews current digital platforms that have been utilised for the teaching and learning of Chemistry. This includes a critical discussion on how effective these platforms have been in improving student performance. It further highlights the different categories of digital tools that have been implemented, and which have been the most successful. The discussion in this chapter concludes with some insights on how digital technologies can be further developed to facilitate teaching and learning in the Fourth Industrial Revolution (4IR)

and artificial intelligence (AI) regime, especially with a focus on the challenging South African education context.

## 2. An Introduction to Digital Learning Resources (DLR)

Digital learning resources (DLRs) are broadly defined as learning tools that are made available to students via an online platform such as Blackboard Learn or using computer-based tools, including multimedia tools and miscellaneous applications (apps). This can take the form of online tests, games, films, audio, and computer simulations (Villasmil, 2024; Marcon & Sehnem, 2024). When implementing DLR, it is imperative to ask three important questions, namely:

1. Which DLR?
2. Why?
3. How?

Furthermore, while some DLRs can be applied across all disciplines, others are discipline-specific. For instance, Blackboard and Moodle can be applied in all disciplines and fields of study, while Aerospace Engineering has its own special software for aerospace digitalisation (Meng *et al.*, 2024). Typically, DLR is categorised into three broad categories, namely

- Digital content, e.g., websites, podcasts, social media, movies, etc.
- Digital tools e.g.: computers, mobile devices, platforms, creative open software etc.
- Digital educational materials, e.g., Pedagogical materials linked to the curriculum, e.g., assignments, additional reading materials, etc. (Villasmil, 2024):

In the context of teaching Chemistry, several digital platforms have become more popular to facilitate the teaching and learning thereof; therefore, this chapter focuses more on the digital platforms that have been applied in the teaching and learning of this discipline and includes a discussion on the influence of these digital technologies on educational pedagogies.

## 3. Web-based Teaching and Learning

Chemistry was just one of many disciplines that had to be delivered online with the onset of the COVID-19 pandemic. This included online classes using Blackboard, Moodle, Google Classroom, Canvas, Edmodo, Flipgrid, Slack, Facebook, WhatsApp groups, Disqus, Microsoft Teams, and Piazza (Iyamuremye *et al.,* 2024) and the uploading of learning materials and online assessments using these platforms. Discussion blogs and forum discussions also featured quite prominently using these platforms. One study, in particular, focused on Web-based discussions on Organic Chemistry in a Rwandan school in which limited student participation and engagement were identified as the key issues (Iyamuremye *et al.,* 2024). An alarming finding from this study was that only 22% of the schools in Rwanda applied Web-based teaching and learning in Organic Chemistry, and this mostly involved the use of WhatsApp, Google Documents, and Google Classroom. Teaching experience. Gender played a key role in the use of Web-based learning, in which male teachers were found to be the most prominent users of such platforms. The limited use of Web-based learning is a cause for concern, especially because this type of learning facilitates collaborative learning where students are provided with opportunities to discuss challenging concepts, ask questions, and engage in problem-solving, active learning, and critical thinking.

Such platforms not only provide students with the tools required to master Organic Chemistry but also provide teachers with opportunities to improve their technological skills (Prestridge, 2019), transition from passive to active learning (Martín-Somer *et al.,* 2024) and improve their methods of assessments and providing feedback (Bragg *et al.,* 2021). Web-based learning also enables teachers to collaborate with their peers on teaching practices and share resources and ideas (Chan *et al.,* 2023). Further benefits of using such platforms include improved teaching techniques, better lesson preparation, and more effective learning experiences for students.

Web-based tools also allow for the integration of audio-visual resources such as videos, which help with the visualisation of abstract Organic Chemistry concepts (Blonder

& Rap, 2017). Difficult concepts like reaction mechanisms and application of organic compounds were better understood by students using platforms such as Moodle, Canvas and Google Classroom (Imanuella & Redhana, 2023). This was especially notable during the COVID-19 pandemic when online teaching and learning became imperative. Moreover, it was shown that students exposed to Google Classroom performed better at Organic Chemistry than those exposed to a traditional classroom (Hashim & Hanibah, 2024). Complex Organic Chemistry concepts can also be better understood using Web-based platforms such as Rain Classroom and WeChat (Guo *et al.,* 2020). In summary, Web-based teaching and learning of Chemistry can help to promote connectivism in the teaching and learning of Chemistry (Goldie, 2016). However, the facilitation and use of such Web-based tools also require access to computers and the implementation of AI in the classroom, leading to the development of computer-based teaching and learning tools which are governed by AI has become imperative.

## 4. Computer-based Digital Tools and Artificial Intelligence

It has been reported that augmented reality (AR) and virtual reality (VR) are very effective in helping students to visualise molecular structures and reaction mechanisms in immersive three-dimensional (3D) environments (Iyamuremye & Ndihokubwayo, 2024; Jiménez, 2019; Mazzuco *et al.,* 2022; Edwards *et al.,* 2019). Furthermore, machine learning (ML) and AI are gaining more popularity in terms of providing strong feedback and adapting learning paths to cater to students' needs based on different learning styles (Ali *et al.,* 2024; Ferrell *et al.,* 2019; Karthikeyan & Priyakumar, 2022; Xiouras *et al.,* 2022). Such tools have, therefore, also promoted effective student engagement and learning outcomes in Organic Chemistry (Iyamuremye *et al.,* 2024). Drug design and drug delivery feature as one of the key areas in Organic Chemistry where AI tools can be used, as outlined in Figure 4.1. Figure 4.2 further enhances the role of ML in understanding aspects of the synthesis and property prediction of nanomaterials - another emerging topic in the field of Organic Chemistry.

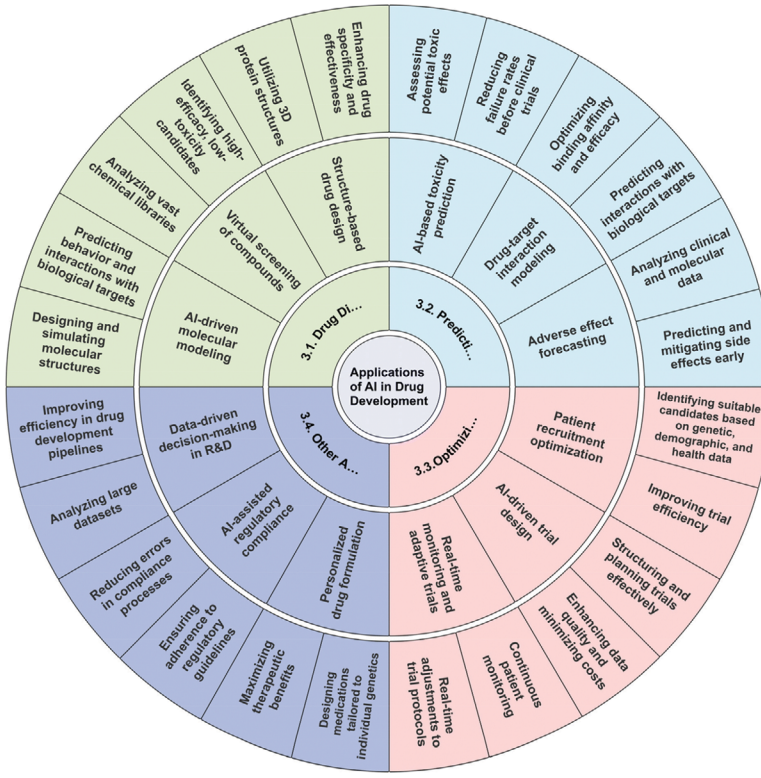



**Figure 4.1:** AI tools in Drug Development (Yu *et al.*, 2025).

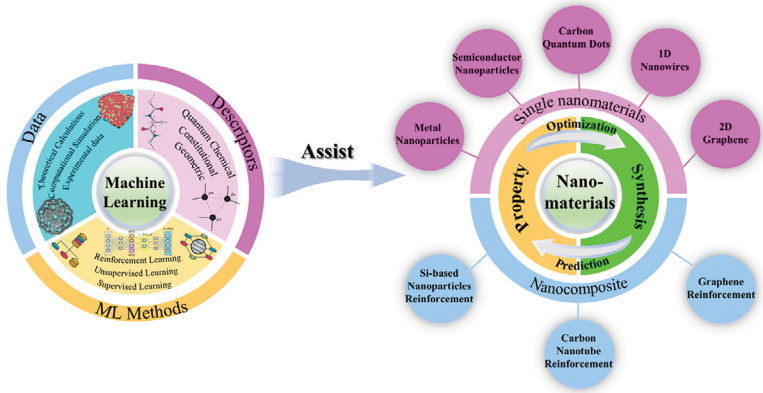



**Figure 4.2:** The Role of Machine Learning in Synthesis and Property Prediction (Diao *et al.*, 2025).

However, Organic Chemistry is by no means the only field of Chemistry which applies the use of ML and AI as enhanced teaching and learning tools. The use of such digital tools is becoming increasingly more popular in Analytical Chemistry as well. Such tools have found their way into laboratory applications. In this sense, Santos *et al.*, (2024) have shown in their review article that digital image colorimetry (DIC) is becoming a very popular analytical technique for chemical quantification of miscellaneous chemical species. This digital technique has proven to be very effective for environmental monitoring, food safety, pharmaceutical analysis, and water quality control, especially when coupled to pre-concentration techniques such as liquid phase microextraction (LPME) and solid phase extraction (SPE). Berasarte *et al.,* (2025) also indicate that DIC coupled with colorimetric paper-based analytical devices (CPADs) and chemometric techniques shows promise for on-site analytical applications for environmental monitoring and point-of-care diagnostics. These digital analytical techniques offer distinct advantages such as good accessibility, simplicity, and cost-effectiveness, and are, thus, a new tool in training Analytical Chemistry graduates effectively.

Physical Chemistry is a third area of Chemistry in which VR has been demonstrated to be an effective learning tool, especially for the teaching of abstract concepts like quantum mechanics. In this sense, Suno and Ohno (2024) have used "virtual hydrogen," which enabled students to visualise hydrogen's atomic orbitals in 3D space and to learn more about the probability density functions and quantum numbers. These authors have also expressed plans to extend this to hydrogen wave functions. Ciriminna *et al.,* (2023) also report on a modelling approach in Nanochemistry which enhances imaging and visualisation and enables educators to design new courses in Electrochemistry.

In fact, Ananikov (2024) has ranked the top 20 most influential AI-based technologies in chemistry as follows:

1. AI-driven Drug Discovery.
2. Big Data and Integrated Data.
3. Automated Laboratory Platforms.
4. Integration of Laboratory Instruments and the Internet of Things (IoT).

5. AI in Spectroscopy and Analytical Method Development.
6. Blockchain in Chemical Supply Chain.
7. Digital Twins.
8. Virtual Laboratories and Augmented Reality.
9. Natural Language Processing (NLP) in Chemical Space.
10. Predictive Toxicology.
11. AI in Environmental Chemistry and Sustainability.
12. Machine Learning in Molecular Design.
13. Smart Control.
14. Deep Learning in Structure-Activity Relationships (SAR).
15. AI-driven High-throughput Experimentation (HTE).
16. Digital Materials Design and Materials Informatics.
17. Data-Driven Chemical Reaction Optimization.
18. Automated Synthesis Planning.
19. Chemoinformatics and Chemical Data Analysis.
20. AI in Quantum Chemistry and Simulations.

Digital technologies have been identified as a useful tool in aligning the curriculum to address the United Nations Sustainable Development Goals (SDGs) (Hariyani *et al.*, 2025). This has become imperative in the teaching of Science, from which Chemistry is not exempted. Such technologies like AI, IoT, blockchain, cloud computing, big data analytics, remote sensing, and geographic information systems (GIS) have the ability to solve global challenges such as poverty, healthcare, climate change, and responsible consumption. Several SDGs that are being addressed by these digital tools are summarised in Table 4.1.

**Table 4.1:** Sustainable Development Goals Supported by Digital Technologies (Hariyani *et al.*, 2025).

| **SDG** | **Digital Technology (DT)** |
|---|---|
| SDG 3 (Supporting Healthcare); SDG 13 (Climate Action) | AI |
| Transparency, Security and Ethical Governance (SDG 16) | Blockchain |
| Real-time monitoring for smart cities (SDG 11) Energy efficiency (SDG 7) | IoT |

| SDG | Digital Technology (DT) |
|---|---|
| Supply chains; agricultural productivity (SDG 2); Disaster Management (SDG 13) | Big Data Analytics |
| Collaboration and Scalability (SDG 9 and 17) | Cloud computing |
| Environmental monitoring and disaster response (SDG 15 and SDG 16) | Remote Sensing and GIS |

Table 4.1 shows that a number of these DTs are associated with the various SDGs; hence, they can be used to align a curriculum to the SDGs. However, these have not been extensively used in the teaching and learning of Chemistry. Some of the reasons could be the digital divide - the gap between individuals, households, businesses, and geographic areas at different socio-economic levels regarding their access to, use of, or impact of information and communication technologies - high cost, data privacy concerns and scarce skills (Hariyani *et al.,* 2025). Solutions to these possible obstacles are provided in the Conclusion and Future Research Perspective Section.

In relation to alignment of the curriculum to the SDGs, the United Nations has also called for the development of education processes that will enable students to acquire the necessary skills and competencies for sustainable development (Marcon & Sehnem, 2024). This includes new teaching innovations for circular economy education. The need for teaching and learning tools such as serious games and simulations has arisen. A literature survey by Marcon and Sehnem (2024) has revealed that 99 innovative games and digital resources have been reported for this purpose. However, adequate information on tutorials linked to these resources, the complexity of the games, the time required to complete activities, and the instructional demand placed on educators is still unavailable.

In the context of teaching and learning Chemistry, attempts at using games as teaching tools include the use of gamified laboratory simulations (Labster) (Sheffield & Kaul, 2024), a hologram-based game using ELEKTRA (Liesatyadharma

*et al.,* 2023), activity cards (Duvarci, 2010), element cycles (Pippins *et al.,* 2011), card and computer games (Rastegarpou & Marashi, 2012) and board games (Antunes *et al.,* 2012). Further reports on the use of game-based tools in the teaching and learning of Chemistry are summarised in Table 4.2.

The following key points can be noted upon examining the information in Table 4.2:

- African countries have not featured amongst the countries implementing game-based learning in Chemistry.
- The game-based learning tools have mostly taken on digital modes.
- The use of these platforms has been implemented to facilitate the learning of a wide array of chemical concepts, including laboratory tools.
- The implementation of game-based learning has been applied both at the high school and university levels.

The primary aim of facilitating the learning of key concepts in Chemistry has been well achieved in these studies. For instance, the study by Liesatyadharma *et al.,* (2023) was aimed at improving the performance of high school students in Analytical Chemistry. This was well achieved, where an improvement in the understanding of key concepts increased from 47% to 65% in pre- and post-experiment quiz scores. Moreover, experts have confirmed that the game was compatible with the high school curriculum.

According to Byusa *et al.,* (2022), in their literature survey, game-based learning promotes "hands on" and "minds on" activities in Chemistry and improves students' understanding of key Chemistry concepts, thereby motivating them to understand the learning content and to learn more effectively while having fun. These mainly take on the forms of computer games and are, therefore, considered to be DTs. However, while digital technologies like simulations and computer games continue to predominate, AI technologies for facilitating teaching and learning in Chemistry still need to be developed. In this sense, 3D printing is the only AI tool that is gaining increasing recognition for enhancing teaching and learning in Chemistry.

**Table 4.2:** Summary of recent studies conducted on the use of game-based tools in the teaching and learning of chemistry

| Country | Game | Chemistry concept(s) | Aim of study | Delivery Mode | Level | Reference |
|---|---|---|---|---|---|---|
| *Singapore* | Legends of Alkhimia | Mixtures, solutes, and immiscible liquids | Enhancing enquiry-based teaching and learning in Chemistry | Digital | High School | (Chee & Tan, 2012) |
| *Taiwan* | 3D Role-playing Game (3D RPG) | Chemical formulae | Motivating and improving student performance in learning chemical formulae | Digital | High School | (Chen *et al.*, 2014) |
| *USA* | Game-Based Approach | Analytical and Organic Chemistry | Facilitating the teaching and learning of Chemistry | Digital and Non-digital | University | (Samide & Wilson, 2014) |
| *Germany* | "Chemory" game | Physical Chemistry | Improving student performance in Physical Chemistry | Digital | University | (Daubenfeld & Zenker, 2015) |
| *Turkey* | Picture Chem | Chemistry laboratory equipment | Improved identification of laboratory apparatus | Non-digital | High School | (Kavak & Yamak, 2016) |

## 5. 3D Printing as a Digital Tool for Teaching and Learning in Chemistry

Three-dimensional (3D) printing is a digital tool that is undergoing constant evolution and has been identified as a technology that is able to enhance the teaching of concepts and skills in miscellaneous disciplines, including Maritime and Port Education (Herazo *et al.,* 2024), Microbiology (Wollmuth *et al.,* 2023), Medicine (Nasr *et al.,* 2024), and Genetics (Papichak *et al.,* 2025). In fact, six key areas in the application of 3D printing in teaching and learning have been identified (Ford & Minshall, 2019). These include:

- Educating students about 3D printing.
- Educating teachers about 3D printing.
- Using 3D printing as a support technology in teaching.
- Production of artefacts to aid learning.
- Creation of technology-assisted tools.
- Support of outreach activities.

In Chemistry, 3D printing has recently been found useful in helping students to visualise molecular shapes, which can be predicted using Valence Shell Electron Pair Repulsion (VSEPR) theory. This is supported by a recent study conducted in Saudi Arabia, in which it was demonstrated that 3D-printed molecular modelling improved students' understanding of molecular geometry, where higher scores were attained in post-tests (Alharbi, 2025). It was, thus, concluded that the incorporation of 3D visualisation tools in Chemistry education helps to enhance conceptual understanding, spatial skills and student engagement and should be included in Chemistry curricula to improve learning outcomes.

Three-dimensional printing has further been reported to support analytical labs with respect to the development of new analytical methods and samples (Horstkotte *et al.,* 2025). This includes the replacement of broken instrumental parts and the fabrication of devices to improve sample preparation, sample handling and detection. Moreover, support for auxiliary elements on commercial instruments can also be 3D-printed. Three-dimensional printing is thus able to provide Analytical

Chemistry students with a fit-for-purpose analytical device which can facilitate their understanding of analytical techniques. Further to this, Tonelli *et al.,* (2019) showed that a Raspberry Pi computer assembled with 3D-printed parts was just as effective as a research-grade spectrophotometer in determining the antioxidant capacity of several bottled teas, while performing diphenylpicryl-hydrazyl (DPPH). Zhang *et al.,* (2022) also developed a modular Laser-Induced Fluorescence detection system (LIFCO) based on LEGO® blocks and 3D-printed blocks. This system offered the distinct advantages of simplicity in structure, ease of assembly, and convenience of use. LIFCO could be applied to general chemical, biochemical, and Analytical Chemistry applications and was, therefore, identified as a useful experimental teaching tool. Vidal and Garcia (2025) have reported the integration of microfluids in 3D printing for electrochemical detection. Moreover, 3D printing can facilitate laboratory automation using autosamplers and robotic hands, thereby minimising human error and enabling students to attain more accurate and precise results (Horstkotte *et al.,* 2025).

Three-dimensional printing is by no means restricted only to undergraduate teaching and training but can also facilitate the teaching and learning of postgraduate and research students. For example, in a review by Khaleghi *et al.,* (2024), it is indicated that 3D printing can facilitate the printing of 2D nanostructures like Molybdenum disulfide ($MoS_2$), which further provides insights on their mechanical strength, conductivity, and therapeutic efficiency for biomedical applications. This can, in turn, provide research students with information on how to modify synthetic procedures for improved biomedical properties. Other applications of 3D printing in supporting student research include the printing of graphene-based materials and metals (Mateti *et al.,* 2023) and have further been applied in technological prototyping and commercialisation. This includes the printing of aluminium, cobalt-based, nickel-based, titanium-based, cobalt-based, stainless steels and miscellaneous polymers including nanocomposites (Alghamdi *et al.,* 2021; DebRoy *et al.,* 2018; Hitzler *et al.,* 2018; Martin *et al.,* 2017; Murr, 2016; Trevisan *et al.,* 2018; Uhlmann *et al.,* 2015). Thus, 3D printing has become a very useful AI tool

in additive manufacturing and can play a key role in equipping graduate Chemistry students with the essential tools to enter the manufacturing sector.

Three-dimensional printing can further enhance laboratory simulations to facilitate practical learning in a remote environment. However, while this has been applied in the Engineering sector (Gomez-del Rio & Rodriguez, 2022; Larriba *et al.*, 2021; Walker *et al.*, 2024) it is yet to be extensively applied in the Chemistry field, where the concept of "frugal twins" for physical experiments is still under investigation (Lo *et al.*, 2024) and is illustrated for Materials Science and Chemistry in Figure 4.3. For instance, high school learners can learn about the laboratory apparatus commonly used in Chemistry from 3D-printed models before they enter university programmes, so that when they are required to learn about volumetric analysis, like titrations, they are familiar with and are able to identify the laboratory glassware which needs to be used.

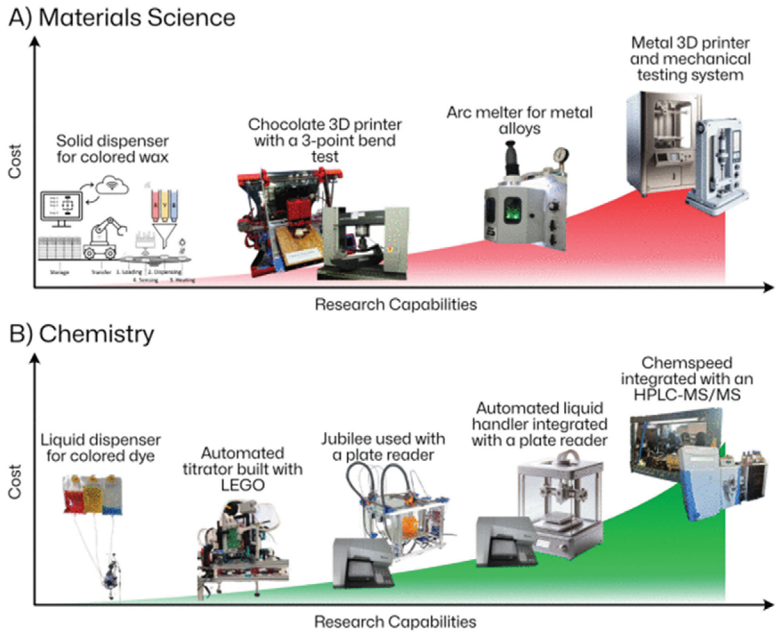



**Figure 4.3:** Schematic Illustration of "frugal twin" concept in Materials Science and Chemistry (Lo *et al.*, 2024).

It has even been suggested that VR can be integrated with 3D printing, especially for additive manufacturing, where the student not only learns about this process on a computer screen but is also able to use physical models to understand the manufacturing process (Javaid *et al.,* 2024). This can further be linked to alignment of the curriculum to the SDGs and bridge the physical and digital divide (Mhlongo *et al.*, 2023). It has also been identified as an effective digital tool for addressing infrastructural deficiencies in the waste beneficiation and manufacturing sector (Muschard & Seliger, 2015).

Thus, there is scope to integrate digital technologies with 3D printing to facilitate the learning of Chemistry, which is extensively discussed in the Conclusion and Future Research Perspective section. However, in an African context, the language barrier remains a problem and impacts on students' comprehension of questions, understanding of theoretical concepts, and response to Descriptive Chemistry questions. This has led to the need for the development of AI tools that are language-based and can even correct grammar whilst providing the student with the necessary conceptual information.

## 6. The Integration of ChatGPT in the Teaching and Learning of Chemistry

Although classified as an AI learning tool, ChatGPT has, in recent years, been identified as an online tool that not only provides students with a platform to gather information on key Chemistry concepts but also assists with sentence construction, grammar, etc. This unique and popular tool was released in November 2022, and since then, it has gained popularity in aiding teaching and learning across various sectors. It has been reported to assist teachers, students and researchers with a variety of tasks (Ma, 2025). Such tasks include material generation, facilitating innovative teaching methods, supporting and streamlining administrative tasks and promoting critical thinking and creativity amongst teachers and students. Additionally, ChatGPT can also provide personalised feedback (Miah *et al.,* 2025).

In the teaching and learning of chemistry, Guo and Lee (2023) conducted a study on implementing ChatGPT for the learning of introductory Chemistry. The ChatGPT activity involved student

engagement in account set-up and orientation, essay writing, output revision and validation. It was noted in this study that the engagement with ChatGPT was successful in terms of enhancing student confidence in asking insightful questions, analysing information, and understanding complex chemical concepts. The students who participated in the study further reported that this exposure to ChatGPT provided them with a platform to gain diverse perspectives and challenged their way of thinking, thereby motivating them to continue using ChatGPT to promote critical thinking skills and recommend this tool to other users. However, this study also reported deficiencies such as poor-quality student comments and difficulties in resource validation, thereby recommending more training of teachers on how to incorporate ChatGPT more effectively in the teaching and learning of Chemistry, with a specific focus on accessing reliable resources and promoting student awareness of privacy and security measures.

A study by Hallal *et al.*, (2023) compared ChatGPT with other AI chatbot tools such as Bard for the teaching of Organic Chemistry. The findings from this study are summarised in Table 4.3.

**Table 4.3:** Summary of the results for the use of ChatGPT in the teaching of organic chemistry (Hallal *et al.*, 2023).

| **Task** | **% ACCURACY** |
|---|---|
| Determining degree of unsaturation from molecular formulae | 80-90 |
| InChi notation | 69-74 |
| SMILES Notation | 64-86 |
| Identifying Functional Groups from Condensed Structures and InChi | 94 (Condensed Structures)<br>50-65 (InChi) |
| Converting Condensed Structures to Molecular Formulas and IUPAC Notation, InChi and SMILES | 73-86 (Molecular Formulae)<br>38 (IUPAC)<br>17-22 (InChI)<br>44-56 (SMILES) |

| Task | % ACCURACY |
|---|---|
| Converting InChi to IUPAC and Condensed Structures | 50-65 (IUPAC)<br>11-28 (Condensed Structures) |
| Converting Smiles to Condensed Structures and IUPAC | 37-42 (Condensed structures)<br>20-25 (IUPAC) |

Table 4.3 shows that ChatGPT gave the best accuracy for identifying Functional Groups from Condensed Structures. In general, ChatGPT gave better accuracy than Bard. Both types of AI chatbots, however, do have their limitations, especially for InChi and SMILE notations. The reading of SMILE notations improved slightly when GPT-4, a newer version of ChatGPT was used. However, there is still room for improvement in areas where ChatGPT has provided lower percentage accuracies.

Despite this, ChatGPT has still been identified as a useful tool in aiding students with the generation of lab reports and assignments. In this sense, Ruff *et al.,* (2024) have reported on the use of ChatGPT version 3.5 to generate laboratory reports and found that good background and context, reasonable procedural description and reasonable data could be generated. Moreover, these authors have also developed assignments that assess the ability of this AI tool to generate laboratory reports and experimental writing in both introductory and advanced Chemistry courses. In these assignments, the students are also expected to discuss the ethical use of AI tools such as ChatGPT in a bid to help them to use these tools responsibly.

Wilkins (2023) highlights the use of ChatGPT in Automated Chemistry, where everything from molecular synthesis and drug design (Gangwal & Lavecchia, 2025) to designing and carrying out a scientific experiment can be achieved. However, this author also highlights one of the demerits of this tool, wherein it can answer questions across disciplines but lacks expert knowledge. Wilkins (2023) highlights this further by discussing how Bran *et al.,* (2024) and their team showed that ChemCrow performed better at synthesis than GPT-4.

In this light, ChatGPT faces competition from many other AI tools, such as El Agente (Zou *et al.*, 2025), which has been reported

to make complex Chemistry concepts like advanced Quantum Chemistry accessible to both experts and non-specialists. KNIME is another competitive AI tool that has been developed to teach core concepts in Medicinal Chemistry, such as examining structure-activity relationships in pharmaceutical drugs (Culp *et al.,* 2024). Besides facing strong competition from new tools that are emerging, ChatGPT also suffers from other flaws that have been widely debated in the literature. It has been recommended that more research on the ethical issues of incorporating ChatGPT in teaching and learning needs to be conducted (Ma, 2025). The need for rigorous ethical considerations has also been expressed by Pharmacy students (Alsakaker *et al.,* 2025). Such ethical considerations include deception pertaining to plagiarism, misuse, which can lead to almost no learning, accountability, or privacy (Memarian & Doleck, 2023). A study conducted by Mei *et al.,* (2025) showed that while ChatGPT reduced difficulty in learning and improved creativity amongst non-English-speakers, it also presented some negative impacts, such as reducing the enjoyment of the task at hand and hampering human creativity by promoting easy content delivery and presenting useful counterpoint ideas. This has led to concerns about moral and ethical considerations on its ability to promote critical thinking skills, amongst students.

A study by Zhang and Zhang (2025) identified a lack in achieving domain-specific tasks by ChatGPT. Other limitations of ChatGPT which have been reported in the literature, include the inability to deal with non-textual semantic reasoning such as mathematical reasoning, poor performance in multi-hop reasoning (Bang *et al.,* 2023), inability to solve named entity tasks (Qin *et al.,* 2023) and poor performance at handling tasks with negative connotations and neutral similarity (Zhong *et al.,* 2023). It is also still unable to outperform SOTA models (Liu *et al.,* 2023) and can limit problem-solving and creative thinking skills (Ubowska & Krowlikowski, 2023).

Thus, while ChatGPT can be an attractive generative AI tool for the teaching and learning of Chemistry, its limitations must be borne in mind when designing learning activities involving this tool. It can be useful for teaching complex Chemistry concepts and even help students to understand and respond to questions based on theory and Descriptive Chemistry. However, educators need

to be mindful of the moral and ethical implications of allowing students to use this tool and assess its impact on plagiarism and reporting false information, which may mislead students. While digital technologies should enhance teaching and learning, their impact on the overall educational development of the student, which includes the ability of the student to think and function independently and apply the knowledge and skills in solving real world problems, still needs to be assessed.

## 7. The Impact of Digital Technologies on Educational Pedagogies

While the need to migrate from traditional teaching and learning methodologies towards digital platforms for teaching and learning is on the rise, the question of how effective such digital tools are in promoting the overall development of the student has arisen. In the previous section, some of the drawbacks of generative AI tools like ChatGPT were highlighted. The key question that has arisen from such drawbacks is: "can such generative AI tools contribute to the overall laziness of students to think and work independently?"

While effective learning of Chemistry has been reported in most studies, the extent to which this enables independent learning in the student has not been extensively reported. However, a lack of teacher training has been identified as one of the setbacks with the use of digital technologies (Sula & Hoxha, 2026). How can teachers assess the impact of such tools when they first need to learn how to use these tools themselves? This argument is supported by a study conducted by Villasmil (2024), which clearly showed that some teachers are in need of "in-service" training on digital technologies to help to relieve them of the stress of learning these first and then applying them in their teaching. The demand for focusing on students' needs when training teachers on how to use digital technologies effectively in the classroom was also expressed.

Recent developments on the use of an open-source software to promote an open pedagogy approach towards the teaching and learning of forensic image processing has, nevertheless, been reported. (Whittaker *et al.,* 2026). Positive feedback was provided

by the students in which they confirmed that this learning tool provided them with the foundational skills which they will be able to build on in future fields of specialisation. The module material used in the open-source software was well-aligned to the Forensic Science Regulator Code of Practice (v2) and these researchers have expressed future plans to develop the module content according to the demands of society and industry. The interdisciplinary approach also facilitates the pedagogical development of the students and career-focused learning.

While the alignment of curricula to the UN's Sustainable Development Goals as per the strategy for Agenda 2030 has become imperative and various digital technologies have been aligned to the SDGs. Marcon and Sehnem (2024) have expressed the need for further developments in innovative games and other digital technologies that provide a holistic, integrated and longitudinal approach towards the teaching of topics such as Sustainability and Circular Economy. These authors further indicate that the development of serious games and simulations can help students to acquire the necessary digital and sustainability skills that are needed for future jobs. Bräse (2024) highlights the use of digital tools in sustainable manufacturing. This involves the use of artificial intelligence algorithms. However, this also requires interdisciplinary collaboration and ethical use of digital tools in chemical research.

The incorporation of AI tools in the teaching of Chemistry provides more opportunities for integrating educational pedagogies than Web-based learning. This is evident from Table 4.3, which clearly shows how various AI tools are aligned with the SDGs. Web-based learning tends to provide more factual information rather than providing students with a skill set that can prepare them for the work environment. However, the integration of Web-based learning with AI tools can be very effective in helping the students to learn basic content and understand difficult concepts whilst developing skills of independent work culture and application-based or contextualised learning.

The ethical use of generative AI tools like ChatGPT still remains a debatable matter. On the one hand, such tools provide students with easy access to information. On the other hand, if such tools do all the work for the student, at what point does

the student engage in independent learning and acquire critical thinking skills for professional development? This is one of the reasons why Bräse (2024) has suggested the integration of such tools with robotics in Chemistry laboratories. However, such advances in the use of these generative AI tools do not necessarily eliminate the importance of the ethical use of such tools. Moreover, in the African context, we need to bear in mind that such language-based tools do not include African languages, so African students may find these difficult to work with.

## 8. Digital Technologies in the African Context

As indicated above, Africa is still not quite aligned with other continents in embracing the digital era of education. Many reasons account for this. One of these reasons is the lack or readiness by teachers to learn how to use and implement these tools in the classroom. This has been highlighted in the study by Sula and Hoxha (2026), in which the demand for in-service training of teachers has been expressed and is further supported by Ojetunde and Ramnarain (2025) who highlight that teacher readiness is a limiting factor based on data gathered from interviewing teachers in Morrocco, South Africa and the Ivory Coast.

Another key contributing factor has been the digital divide, which has placed students living in rural areas at a disadvantage because of poor Internet access. Poverty also plays a role where students can barely survive without basic needs like food and water but are expected to have devices like laptops, tablets and smartphones to engage in digital learning. As a result, many universities and sponsors have realised that such devices need to be provided to the students in a bid to enable them to engage in active digital learning. The disadvantage of this is that not all universities and sponsors have enough financial resources to cater for every needy student.

In fact, only two studies thus far have alluded to developments in using digital tools for the teaching of Chemistry in Africa. These include the study by Iyamuremye *et al.,* (2024), which highlights the use of Web-based learning for the teaching of Organic Chemistry in Rwanda and the study by Sula and Hoxha (2026), which focused on the integration of Content and

Language Integrated Learning (CLIL) with digital tools in Algeria. Studies in other African countries have been limited and restricted mainly because of teacher perspectives on the implementation of digital technologies in which the availability of digital tools to teachers was identified as another stumbling block to the full implementation of digital teaching and learning in Science (Ojetunde & Ramnarain, 2025).

Most reports on the implementation of digital technologies have focused mostly on schools. This has brought about the need for more investigations into the implementation of digital teaching and learning of Science modules like Chemistry in higher education institutions in Africa as well. However, before this is fully investigated, other underlying factors contributing to slow implementation of digital technologies for the teaching of science need to fully examined (Ojetunde & Ramnarain, 2025).

## 9. Conclusion

This chapter has provided an overview of all the digital tools that are currently available and that have been used for the teaching and learning of Chemistry. These have ranged from Web-based platforms to game-based learning, 3D printing and generative AI tools. The various modes of digital technologies available are summarised in Figure 4.4.

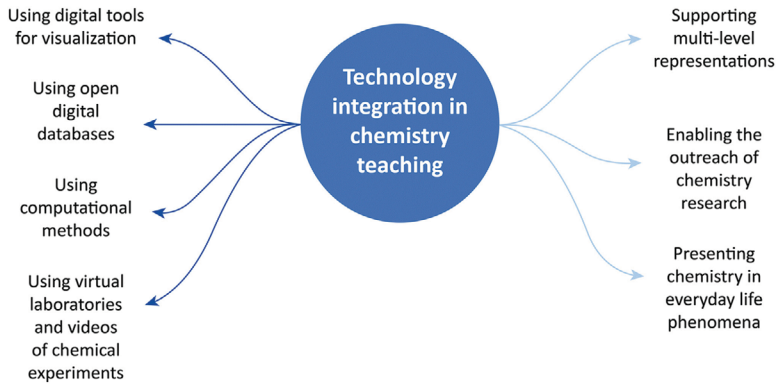



**Figure 4.4:** A summary of the various digital technologies available for teaching of chemistry (Aroch *et al.*, 2024).

While there is a myriad digital tools that have been reported and have shown successful results, the implementation of such tools in the teaching and learning of Chemistry in the African continent is still limited. This is mainly caused by the digital divide, lack of available resources such as reliable Internet and digital devices, and teachers not being well-trained with digital technologies. Most South African schools and universities face the challenge of hosting learners and students from rural areas where reliable Internet facilities are scarce. Poverty has also played a vital role in some students not being able to afford laptops, tablets and smartphones, leading to the digital divide.

Moreover, besides ChatGPT and similar AI tools, many of the digital tools do not adequately cater for students who do not speak English as a first language and may not have studied Chemistry in English. The integration of 3D printing with AI tools, such as virtual reality, still needs more development.

Nevertheless, digital tools have been very effective in helping students to visualise difficult concepts especially in Organic Chemistry, providing platforms for students to engage with virtual laboratories and experiments whilst using these tools to generate laboratory reports, etc. However, the student's own work and the integrity of the work produced by the student cannot be compromised. Digital tools must, therefore, be carefully devised where student learning is enhanced but the student still produces original work.

The factors governing the implementation of digital tools in Africa still need to be unravelled. Thus far, only lack of teacher readiness, language barriers, poverty and the digital divide have been identified as the key contributors. There is still a need to identify more factors that can contribute to the slow progress in the implementation of digital technologies in the teaching of Chemistry.

Moreover, studies conducted to date are more teacher-focused than student-focused. Students' perceptions and experience with digital technologies can provide us with feedback on how to improve their learning experience. There is also a bias towards targeting schools rather than higher educational institutions.

The following future research perspectives are, therefore, proposed:

- More studies on the use of digital tools and how they impact the teaching and learning of Chemistry in the African continent with an emphasis on identifying more factors that have contributed to slow progress and how to overcome these for more effective teaching and learning.
- Development of digital teaching and learning tools to bridge the language barrier, e.g., games or interactive videos and animations, which can enable students to learn Chemistry in their mother tongue.
- More studies on the integration of 3D printing with other digital tools, e.g., printing of board game tools and the periodic table.
- More interactive cartoons and videos which can serve as e-notebooks and replace mundane textbook and notebook learning and facilitate the learning of Descriptive Chemistry.
- Further improvements to generative AI tools like ChatGPT to enable students to learn chemical concepts and Descriptive Chemistry without engaging in plagiarism and compromising on moral and ethical issues.
- Further studies on higher education case studies and how these impact on the professional development and employability of university graduates.

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# Chapter 5

# Pedagogical Benefits of Integrating Computational Tools for Teaching Biochemistry and Biotechnology Courses at Undergraduate Level to Enhance Student Learning

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## Abstract

Studying Biochemistry and Biotechnology at undergraduate level can present a daunting challenge for students, yet these fields remain deeply engaging when taught effectively. The subject matter is inherently complex, requiring a strong foundation in Biology and Chemistry as well as the ability to comprehend intricate molecular processes. A persistent challenge lies in the gap between theoretical instruction and practical application, where limited access to physical laboratories and advanced computational resources restricts opportunities for active learning. However, with the necessary effort and the adoption of proper strategies, students can succeed and find the area exciting and gratifying. Because of the benefits of flexibility, scalability, technological integration, and interactive visualisations, interest in virtual laboratory simulations as a teaching tool is still increasing. This chapter highlights the pedagogical benefits

of introducing computational tools early in undergraduate Biochemistry and Biotechnology education and provides guidance for instructors on the software resources required to successfully integrate these approaches, thereby contributing to sustainable and inclusive education in alignment with the Sustainable Development Goals.

**Keywords:** Active learning, Biochemistry, Biotechnology, Computational tools, Constructivism, Sustainable Development Goals

## 1. Introduction

Undergraduate education in Biochemistry and Biotechnology plays a critical role in preparing students for careers in biomedical research, environmental sustainability, and agricultural innovation. These fields require a robust understanding of molecular interactions, cellular processes, and experimental methodologies, yet they are often regarded as daunting because of the conceptual density and interdisciplinary scope involved (Lee *et al.,* 2020). Students must develop fluency in Chemistry, Biology, and Data Interpretation, sometimes simultaneously, making early engagement and effective scaffolding essential to their success. As educators grapple with increasing class sizes, resource limitations, and curricular reform, technological tools are emerging as powerful allies in fostering student comprehension, autonomy, and engagement (Chiu *et al.,* 2021). This motivation also reflects broader pedagogical challenges, particularly the need to balance hands-on, enquiry-driven laboratory experiences with online and computational learning formats.

Amongst these tools, virtual laboratory simulations and bioinformatic platforms stand out for their scalability, repeatability, and adaptability to different learning environments. These simulations replicate complex wet-lab procedures, enabling students to interactively explore molecular phenomena without the physical constraints of traditional laboratories (Makransky *et al.,* 2019). When paired with molecular visualisation tools and sequence analysis software, students can model

biochemical pathways, predict protein structures, and manipulate genomic data in ways that strengthen both their theoretical and practical understanding. This interactive format improves retention and stimulates curiosity, helping students to move beyond rote memorisation to a more authentic scientific mindset (De Jong *et al.*, 2013).

Early exposure to bioinformatic and computational tools at the undergraduate level offers distinct pedagogical advantages. By simulating workflows common in research laboratories, these tools instil computational literacy and foster critical thinking, skills now essential in the life sciences (Cummings & Temple, 2010). For example, students can perform homology modelling, analyse protein–ligand docking, or study genome alignments, all processes that mirror the methodologies used in fields such as Structural Biology and Systems Genetics. Visual analytics help to bridge abstract biochemical concepts and concrete representation, promoting deeper understanding and enabling learners to see molecular mechanisms in action (D'Costa *et al.*, 2017). Furthermore, when students explore these digital tools collaboratively, they develop transferable skills in communication, data interpretation, and scientific reasoning, all of which align with national science education goals (Mihram & Mihram, 2011). Situating this transformation within the discourse of the Fourth Industrial Revolution (4IR) emphasises its relevance to emerging technologies such as artificial intelligence, machine learning, and advanced molecular modelling, which are reshaping both research practice and educational expectations.

This chapter explores the integration of bioinformatic and computational visualisation tools into undergraduate biochemistry and biotechnology modules, particularly as a strategy for enhancing engagement and deep learning. It offers a practical guide for instructors to select appropriate software tools, such as UCSF Chimera, BLAST, RCSB PDB, and SnapGene, based on their alignment with course objectives and useability within diverse classroom contexts (Wang & Bai, 2022). Additionally, the chapter addresses challenges in implementation, such as

instructor training and digital equity, while showcasing the broader impact of these tools on student motivation, retention, and self-efficacy. Therefore, this reflective report is guided by three key objectives: (1) to evaluate how computational tools can effectively balance traditional laboratory-based learning with digital pedagogy; (2) to position Biochemistry and Biotechnology education within the wider context of the 4IR; and (3) to examine whether the integration of technology should be viewed as a temporary adaptation to the coronavirus disease 2019 (COVID-19) pandemic or as a lasting institutional innovation. In doing so, it argues for a pedagogical shift, one that treats technological integration not as ancillary, but as foundational to the development of modern bio-scientists.

## 2. Integrating computational pedagogies into biochemistry and biotechnology courses

Computational techniques, such as molecular dynamic (MD) simulations, were once thought to be the domain of Physical Chemistry. Consequently, some may question whether the technique is appropriate for use in Biochemistry and Biotechnology courses. The growing importance of these computational methods in current biochemical research is one of the reasons that it is critical to introduce Biochemistry and Biotechnology students to these techniques. There are numerous published works on classroom or laboratory exercises that use MD simulations specifically created for Physical Chemistry courses. While students may benefit from a greater comprehension of the mathematical modelling of chemical systems taught in Physical Chemistry classes, it is not guaranteed that they will gain a strong conceptual understanding of MD. This is especially true, as MD primarily predicts the motion of atoms and molecules over time using concepts from classical mechanics, such as Newton's Law (Albrecht, 2014; Saiz & Tarazona, 1997).

We have realised that students often find it difficult to relate their understanding of biological molecules to their functions. This has also been reported in several studies, with students often struggling to create a mental three-dimensional (3D) picture of various molecules (Barnea & Dori, 1996;

Marbach-ad & Stavy, 2000; Wu & Shah, 2004; Duncan & Reiser, 2007; Van Mil *et al.,* 2016). For this reason, the utilisation of computational tools enhances learning, makes it more engaging, and facilitates better visualisation and comprehension of chemical structures, characteristics, and interactions. There is a variety of popular molecular visualisation programmes like PyMOL, VMD, Rasmol, or Swiss PDB Viewer that allow students to see the structures of proteins, nucleic acids, and other macromolecules. Although these visualisation tools only provide students with a static view of molecular structure, such as a conformation of a protein captured in a 3D structure, students have the potential to learn and engage more from a representation that they are actively involved in creating, instead of being passive observers.

Recent international case studies highlight how digital and hybrid pedagogies have been adopted in Science, Technology, Engineering and Mathematics (STEM) and architectural education during 2020 to 2024, particularly in response to coronavirus disease 2019 (COVID-19). For example, hybrid studio models in Europe and Asia combined synchronous online collaboration with asynchronous design tasks, demonstrating improved student autonomy and reflective practice (Balbo, 2024; Estrina, 2021). In biotechnology education, similar hybrid approaches have been reported in South Africa and India, where virtual labs and bioinformatic platforms were integrated to mitigate resource constraints while maintaining experiential learning outcomes (Ngema & Motlhabane, 2025; Radhamani *et al.,* 2018). These examples emphasise the global relevance of computational tools in bridging disciplinary gaps and sustaining student engagement.

Conceptually, the integration of computational tools aligns with **constructivist learning theory**, which emphasises active knowledge construction through interaction with digital environments (Jonassen, 1999; Piaget, 1972). Likewise, **connectivist learning theory** situates learning within networks of digital resources and collaborative communities, making bioinformatic platforms ideal for fostering distributed knowledge and peer-to-peer learning (Siemens, 2005). These theoretical perspectives provide a guiding framework for platform design, ensuring that students are not passive recipients of information but are active participants in constructing and connecting knowledge.

From a Scholarship of Teaching and Learning (SoTL) point of view, computational pedagogies advance: 1) the teaching practice and academic research in education (Tight, 2018) by incorporating technology-driven innovation (Incorporating these interactive digital resources, modelling, and simulations into the teaching and learning process, they offer innovative ways and resources that can enhance student engagement, comprehension, and retention); 2) Interdisciplinary learning (McKinney, 2013) (using computational methodologies, instruction can span several fields such as Computer Science, Biology, and Chemistry, resulting in more comprehensive and applicable learning experiences that mirror real-world problems); and 3) Supports remote and flexible learning (Makinde, 2025) (blended and online learning environments are made possible by computational pedagogies, increasing accessibility and adaptability - a vital feature in situations like the COVID-19 pandemic).

Finally, attention to **user experience (UX) design** and digital pedagogy is critical in justifying platform choices. Principles such as intuitive navigation, visual clarity, and interactive feedback loops enhance useability and reduce cognitive load, thereby supporting deeper learning (Norman, 2013; Laurillard, 2012). For instance, molecular visualisation tools with customisable interfaces allow students to manipulate structures directly, fostering experiential learning and situated cognition. Embedding UX considerations ensures that technological integration is not only functional but pedagogically meaningful.

## 3. Computational software resources that can be integrated to effectively teach Biochemistry and Biotechnology at undergraduate level

Given the cost of some of the hardware and software previously used and still in use today, instructors may be understandably concerned about their ability to acquire the computational resources required to introduce students to these visualisation tools. Fortunately, most of these resources have become less expensive over time. In fact, students can now use software that they can download for free (Table 5.1). Free interactive computational visualisation tools can be integrated in teaching and will also be discussed in more detail in this section.

**Table 5.1:** Examples of free software packages for visualising molecular structures.

| Software package | Website |
|---|---|
| The National Center for Biotechnology Information (NCBI) | https://www.ncbi.nlm.nih.gov/ |
| Clustal Omega<br>Multiple Sequence Alignment (MSA) | https://www.ebi.ac.uk/jdispatcher/msa/clustalo |
| SOPMA (Self-Optimized Prediction Method with Alignment) | https://npsa.lyon.inserm.fr/cgi-bin/npsa_automat.pl?page=/NPSA/npsa_sopma.html |
| SWISSMODEL | https://swissmodel.expasy.org/ |
| Swiss-PdbViewer (DeepView) | https://spdbv.unil.ch/ |
| AutoDock Vina | https://vina.scripps.edu/ |

## 3.1. The National Center for Biotechnology Information (NCBI)

The NCBI is aimed at facilitating access to a vast amount of genomic and biological data in order to advance Science. The platform (Figure 5.1) provides various computational resources and creates and manages Molecular Biology databases and information systems, such as the GenBank sequence database (Benson *et al.,* 1998), PubMed® and BLAST (Altschul *et al.,* 1990) services. It was set up to perform four major tasks and these include:

(i) Make it easier for Biotechnology, Biochemistry and Molecular Biology researchers as well as medical professionals to use databases and software.
(ii) Develop automated systems for the evaluation and storage of genetic, biochemical, and Molecular Biology knowledge.
(iii) Investigate cutting-edge computer-based information processing techniques for examining the composition and operation of biologically significant molecules.
(iv) Organise global information-gathering activities related to Biotechnology.

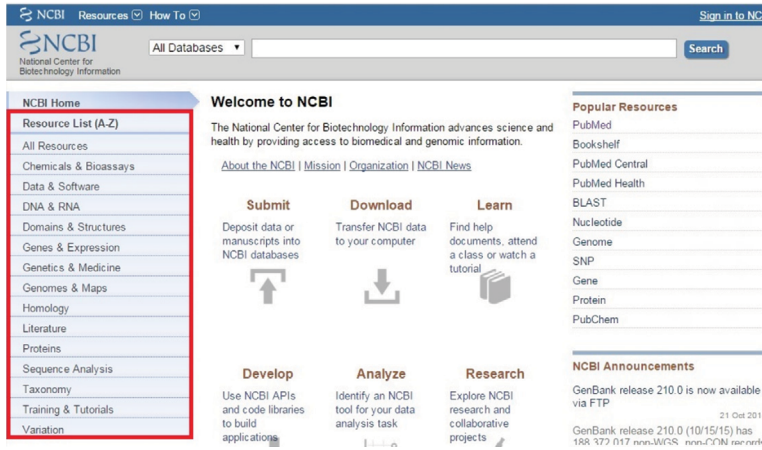



**Figure 5.1:** Represents the homepage of NCBI displaying various computational resources (Jenuth, 2000).

## 3.2. Clustal Omega Multiple Sequence Alignment (MSA)

A popular command-line program for creating multiple sequence alignments (MSAs) of DNA/RNA (deoxyribonucleic acid / ribonucleic acid) or protein sequences is called Clustal Omega (Figure 5.2). With the aid of a guide tree produced by pairwise sequence comparisons, it employs a progressive alignment technique. For increased accuracy, it also makes use of Hidden Markov Models profile-profile alignment techniques (Sievers *et al.*, 2011). Clustal Omega aids in the alignment of genomic sequences, which is crucial for determining regulatory regions and comprehending the structure and function of genes as well as determine the evolutionary relationships between various

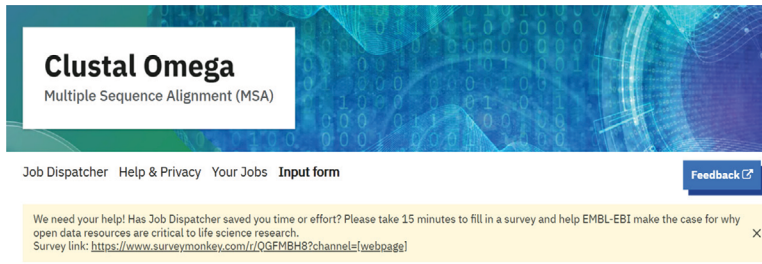



**Figure 5.2:** The homepage of Clustal Omega sequence alignment tool (Higgins, 1994).

organisms or genes (Blackshields *et al.*, 2010). Conserved areas of proteins (Figure 5.3), which frequently correlate to significant structural or functional domains, can also be revealed through alignments (Sievers *et al.*, 2014).



**Figure 5.3:** Sequence alignment analysis of retrieved sequences of an enzyme using Clustal Omega database (Higgins, 1994).

## 3.3. SOPMA (Self-Optimized Prediction Method with Alignment)

Protein secondary structure can be predicted computationally using SOPMA. SOPMA makes use of the fact that proteins with comparable sequences, or homologous proteins, typically have secondary structures that are similar (Figure 5.4). It operates by:

(i) Looking for homologous sequences in a database of proteins.
(ii) Creating a multiple sequence alignment between the homologs and the query protein.
(iii) Considering the conservation of structure amongst the aligned proteins, the secondary structure of the query protein is predicted using the aligned sequences.

Based on the amino acid sequence, secondary structure prediction in proteins seeks to identify local, regular structures (such as beta-sheets and alpha-helices). This is an essential step in comprehending the function of proteins (Heringa, 2000).

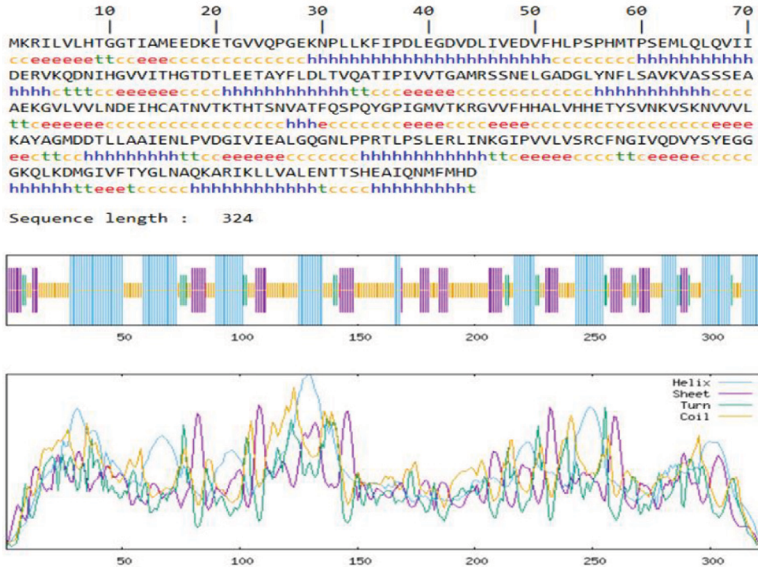



**Figure 5.4:** Output result of SOPMA database showing the various secondary structure indices of a protein (Geourjon & Deleage, 1995).

## 3.4. SWISS-MODEL

A completely automated Web-based tool for modelling protein structural homology is called SWISS-MODEL (Figure 5.5). It predicts a protein's three-dimensional structure using a comparison method based on the amino acid sequence. A protein's structure can reveal information about its function, interactions with other molecules, and function within cellular processes (Waterhouse *et al.,* 2018).

## 3.5. AutoDock Vina

AutoDock Vina, a molecular docking tool that can be easily accessed, simulates the binding of a ligand to a protein target to estimate the best stable binding conformation (pose) and affinity. Molecular docking is commonly used to predict the binding orientation of various substrates and small molecules (drug candidates) to their biomolecular targets (e.g. protein, carbohydrate, and nucleic acid) and assess their potential binding characteristics (Figure 5.6) (Guedes *et al.,* 2014; Eberhardt *et al.,* 2021).

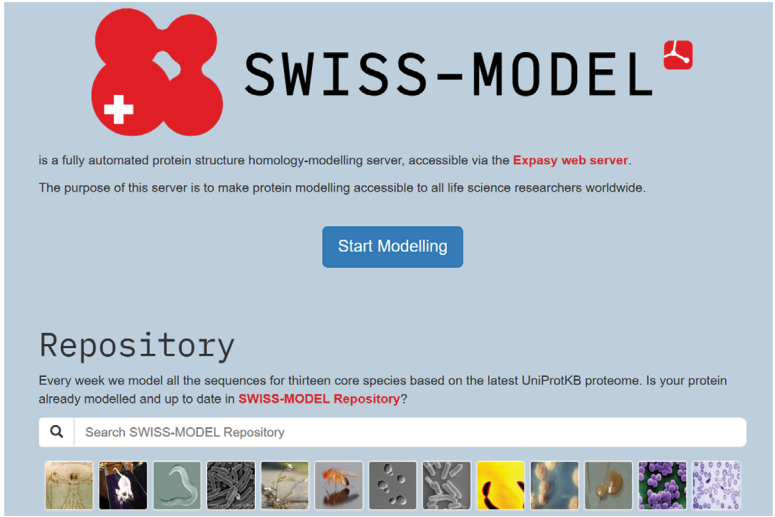



**Figure 5.5:** SWISS-MODEL server homepage which is accessible via Expasy Web server (Waterhouse *et al.*, 2018).

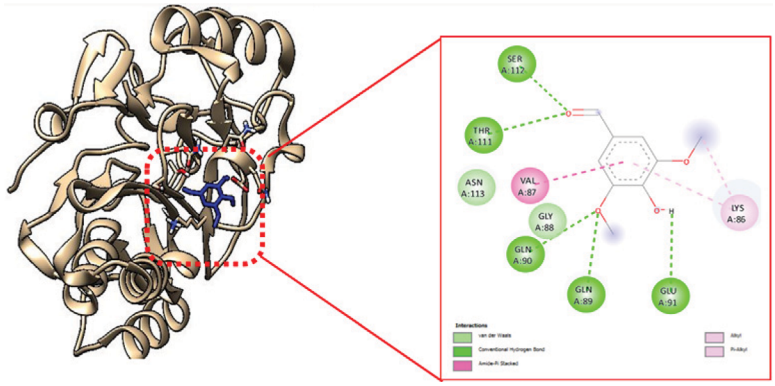



**Figure 5.6:** Output result of AutoDock Vina, displaying the predicted binding orientation of a ligand (Guedes *et al.*, 2014; Eberhardt *et al.*, 2021).

## 4. Linking computational pedagogies to learning theories

The use of computational pedagogies in the teaching of undergraduate Biochemistry and Biotechnology is supported by well-established learning theories that emphasise the importance of active engagement, meaning-making, and social interaction.

The fields of biochemistry and biotechnology require students to make sense of complex, abstract, multiscale phenomena that are not directly observable. These include molecular interactions, enzymatic mechanisms, and dynamic cellular processes. The use of static diagrams and symbolic representations aids in helping students to develop understanding in these fields. Learning theories, especially constructivism and social constructivism, provide a stronger theoretical guide for the use of computational pedagogies in teaching Biochemistry and Biotechnology because they emphasise active knowledge construction and collaborative meaning-making as essential aspects of learning (Piaget, 1972; Fosnot, 2013).

From the constructivist perspective, learning is an active process whereby individuals construct knowledge by relating new experiences to their existing mental structures. Learning is not the passive reception of knowledge from an external source; learning is an active construction of knowledge that is built on the learner's existing mental structures. The use of computational pedagogies in teaching Biochemistry and Biotechnology is especially relevant because learning in these fields requires students to make sense of complex molecular systems that cannot be directly experienced. However, computational pedagogies, including molecular visualisation programs, protein structure modelling programs, and molecular sequence analysis programs, enable learners to interact with representations of complex molecular systems. Through interactive engagement with molecular models, learners can actively construct mental representations that enable deeper understanding of complex molecular systems (Barnea & Dori, 1996; Wu & Shah, 2004).

Constructivist learning environments place significant emphasis on the importance of enquiry, exploration, and problem-solving as major factors in conceptual development. Computational pedagogies align well with this model, as they enable learners to participate in scientific practices that are authentic and similar to those used in current biochemical and biotechnological research. For example, learners could use prediction software for protein secondary structure, identify conserved motifs using multiple sequence alignment, or use

ligand binding software for evaluating docking. These activities enable learners to move beyond memorisation and engage in an epistemic relationship with scientific knowledge, leading to the development of scientific reasoning and conceptual understanding (Duncan & Reiser, 2007; Sandoval, 2005).

The use of visualisation is significant in constructivist learning, particularly in the molecular sciences. Studies have shown that learners have difficulty in creating accurate mental models of molecular concepts when these concepts are explained using symbolic or textual representations (Marbach-Ad & Stavy, 2000; Van Mil *et al.,* 2016). Interactive computational visualisation enables learners to externalise their mental models and test them by making connections between abstract concepts and concrete models. Gilbert (2008) suggests that visualisation should be viewed as a metacognitive skill, which is particularly relevant in the fields of Biochemistry and Biotechnology, as learners must be able to translate concepts across various levels of understanding.

Although the constructivist model is focused on the individual's process of meaning-creation, social constructivism is a continuation of this model that emphasises the importance of social interactions in the learning process. According to this model, cognitive development happens first on the social level before moving on to the individual level (Vygotsky, 1962; Vygotsky, 1978). Learning in the undergraduate Science classroom is not just about the individual but also about the social interactions that happen in the learning process. Computational tools can be effectively utilised to implement social constructivist learning in the classroom.

Group-based computational activities, such as collaborative protein sequence analysis or discussion of molecular docking outcomes, facilitate students' ability to clarify their thinking, negotiate meaning, and question one another's thinking. This process of conceptual refinement occurs as students are exposed to other students' thinking, which may differ from their own (Rogoff, 1994; Mercer, 2000). Shared computational artefacts, such as molecular models or alignment results, facilitate discussion and collaborative investigation, helping students to ground their thinking in concrete representations of molecules

or other Biochemistry-related topics. This approach is consistent with the constructivist idea of learning as participation in a community of learners, whereby knowledge is constructed through social interaction rather than through the accumulation of facts by individuals (Rogoff *et al.,* 1998).

Related to both constructivist and social constructivist theory is the idea of scaffolding, which refers to the systematic assistance provided by teachers to learners to facilitate their ability to complete tasks that are beyond their current capabilities (Wood *et al.,* 1976). In computationally rich Biochemistry and Biotechnology courses, scaffolding involves careful task design, with tasks being made progressively more cognitively and computationally demanding. For example, students may be provided with tutorials on molecular visualisation, progressing to more open-ended modelling or docking activities. Computational tools are effective scaffolds because they offer students feedback on their progress, enabling them to monitor their own learning and adapt their strategies as needed (De Jong *et al.,* 2013).

The cognitive apprenticeship theory further supports the pedagogical rationale for the use of computational tools in the education of undergraduate Science students. Cognitive apprenticeship is a model of learning that focuses on the importance of guided participation in practice, in which the thinking of experts is made explicit and gradually transmitted to the learner (Collins *et al.,* 1989). In this model, the teacher or the expert acts as a role model by demonstrating the use of computational tools in the analysis of molecular data, interpretation of results, and assessment of limitations. As the student becomes more proficient in the use of the tools, they are encouraged to take more responsibility in the process, from observation to practice. This not only helps the student in understanding the subject matter but also in the construction of professional scientific identity, as the student gradually starts to view themselves as capable participants in the practice of Science (Collins, 2006).

Moreover, the use of computational tools in the education of Science students also helps in the construction of metacognitive awareness, as the student is encouraged to reflect

on the processes and limitations of computational modelling. As the student compares the predicted structures with the experimentally determined models or assesses the limitations of the algorithms in the docking process, they are encouraged to reflect on the nature of scientific knowledge. Such reflection helps in the construction of a more advanced understanding of Science as a model-based process rather than a set of truths (Sandoval, 2005; De Jong *et al.*, 2013). Such epistemic awareness is one of the most important outcomes of Science education in the modern world, especially in the rapidly advancing field of Biotechnology.

Collectively, these learning theories offer a comprehensive and sound basis upon which to integrate computational tools within the curriculum of undergraduate Biochemistry and Biotechnology education. The learning theories of constructivism, social constructivism, scaffolding, and cognitive apprenticeship offer an explanation for why computational learning strategies are not only technological innovations but, in fact, powerful learning strategies that facilitate engagement, collaboration, and ways of thinking characteristic of particular disciplines. The learning theories offer a sound basis upon which to integrate computation within the curriculum of undergraduate Biochemistry and Biotechnology education.

## 5. Linking computational pedagogies to United Nations' Sustainable Development Goals (SDGs)

Using computational pedagogies can enable engagement with a number of sustainable development goals. Through the development of critical thinking, creativity, and problem-solving skills, these computational pedagogies can enable students to tackle intricate global issues and link to specific SDGs which include:

(i) SDG 4: Quality Education - Computational thinking is becoming more widely acknowledged as critical 21st-century competency, which directly supports the objective of guaranteeing inclusive, equitable, high-quality education.

(ii) SDG 9: Industry, Innovation, and Infrastructure - The development of innovative and technologically advanced skills is essential for creating resilient infrastructure and advancing sustainable industry, and computational pedagogies can foster these abilities.

(iii) SDG 17: Partnerships for the Goals - In order to tackle difficult global issues, computational pedagogies can promote cooperation and knowledge exchange, promoting interdisciplinary approaches.

## 6. Conclusion

As an instructor/educator, it is an honour to shape the thoughts of the next generation of influential members of society who are on the verge of becoming the next generation scientists. However, to effectively shape these individuals and impart knowledge calls for innovative teaching methods, lifetime learning and constant growth. By utilising computational pedagogies can create dynamic, interactive learning environments where students can simulate scenarios and develop their skills in a collaborative setting. But most importantly, by integrating computational pedagogies into education, we can equip learners with the skills and knowledge needed to address the complex challenges outlined in the SDGs and build a more sustainable future for all.

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Chapter 6

# Gamified assessments in molecular-based Biochemistry modules: Student perceptions and engagement outcomes with digital quiz platforms

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## Abstract

Grounded in Self-Determination Theory and active learning principles, this study examines the pedagogical transformation achieved through integrating gamified learning platforms, Kahoot and Quizizz (now called Wayground), within third-year Molecular Biology and Molecular Physiology modules at the University of Johannesburg. Despite growing evidence for technology-enhanced learning in STEM education, significant gaps remain in understanding how gamified assessments address persistent engagement challenges in complex molecular biology contexts, particularly within resource-variable South African higher education settings Initially started because of the need to address student passivity and engagement challenges during the COVID-19 pandemic online learning, the implementation evolved into a systematic pedagogical approach grounded in self-determination theory, cognitive load theory, and active

learning principles. Using a mixed-methods approach with 27 student participants across approximately 200 students per module between 2020 and 2024, the study evaluated the impact of these tools on student engagement, comprehension, and motivation. Survey results (n=27) revealed that 92.31% of students agreed that gamified tools made Molecular Biology and Molecular Physiology concepts more engaging, with 96.15% finding sessions enjoyable and 88.46% reporting improved comprehension. Qualitative analysis of open-ended responses identified three key themes: enhanced engagement through interactive and competitive elements, improved understanding through immediate feedback, and practical concerns about technological infrastructure and question design. This study demonstrates how strategic gamification can transform passive learning environments into psychologically safe spaces where students actively participate without fear of judgement. The findings provide evidence for the effectiveness of game-based learning in complex STEM modules and offer practical insights for educators seeking to enhance student engagement while maintaining academic rigour. This pedagogical transformation demonstrates innovative teaching practices that bridge the gap between complex Molecular and Biochemistry content and student comprehension through thoughtful technological integration.

**Keywords:** Gamification, Kahoot, Molecular Biology education, Quizizz, Student engagement

## 1. Introduction

Present-day higher education faces mounting pressure to address declining student engagement, particularly in Science, Technology, Engineering and Mathematics (STEM) disciplines where complex theoretical content often creates barriers to active participation (Freeman *et al.,* 2014). Gamification, characterised by the integration of game design elements into non-game environments, has gained popularity in classrooms because of its potential for increased engagement and enjoyment compared to traditional lecture-based teaching methods (Zeng *et al.,* 2024). The integration of gamification into educational settings has

gained recognition for its potential to boost student motivation, engagement, interest, and learning outcomes, though research has produced mixed results regarding consistent academic achievement (Sailer & Homner, 2020).

Molecular Biology education presents pedagogical challenges because of the abstract nature of cellular processes, complex biochemical pathways, and the need for students to visualise molecular interactions that occur beyond direct observation (Brownell *et al.,* 2014). Active, hands-on learning has been shown to improve educational outcomes in STEM subjects. However, implementation of hands-on activities for teaching Biology has been more challenging than in other Science disciplines because of challenges associated with the use of living cells (Huang *et al.,* 2022). Traditional lecture-based approaches in Molecular Biology often result in passive learning environments where students struggle to connect theoretical concepts with practical applications, leading to surface-level understanding rather than deep conceptual mastery. This traditional method, characterised by one-way knowledge transfer, is known to induce compliance and passivity in students (Goel, 2024). While providing a structured means of content delivery, such approaches frequently lead to limited student engagement and a superficial grasp of concepts. The coronavirus disease 2019 (COVID-19) pandemic intensified these educational challenges, forcing rapid transitions to online learning environments that further amplified student disengagement. In the South African higher education context, this transition was particularly complex, with students facing disparate access to reliable Internet connectivity, appropriate devices, and conducive learning spaces. These infrastructure constraints, combined with varying levels of digital literacy, necessitated pedagogical innovations that could function across diverse technological contexts while maintaining academic rigour and inclusive participation. This led to an urgent need for innovative digital pedagogical strategies (Alonso & Schroeder, 2020). This crisis catalysed widespread experimentation with technology-enhanced learning approaches, including gamified assessment platforms that could maintain student engagement despite physical separation.

Recent meta-analytical research supports the effectiveness of gamification in educational contexts (Li *et al.,* 2023; Sailer & Homner, 2020). Specifically, Sailer and Homner's (2020) meta-analysis revealed a significant effect of gamification on motivation to learn, whilst several studies have demonstrated that gamification can positively influence student motivation and engagement. Huang and Hew (2018) found that gamification elements such as badges and leaderboards significantly increased students' behavioural engagement in flipped learning environments. A significant improvement in learning performance for students in the gamified condition was observed in recent STEM education research, providing compelling evidence for the pedagogical value of game-based learning approaches (Subhash & Cudney, 2018). This aligns with the understanding that game-based learning (GBL), which intentionally uses games to fulfil learning objectives, positively affects student engagement. This engagement is a key factor in improving learning outcomes. Furthermore, various forms of GBL, such as serious games (SGs), have been successfully implemented across a wide range of subjects, including Health, Business, Science, Military, Computer Science, Mathematics, and Biology. This widespread application across diverse fields further substantiates the broad utility and effectiveness of integrating GBL strategies into educational contexts, particularly in STEM disciplines where complex content can benefit from enhanced engagement (Wiggins, 2016).

The integration of gamified platforms in higher education aligns with broader Fourth Industrial Revolution (4IR) transformations, reshaping pedagogical practices globally. While these platforms currently operate as standalone engagement tools, they represent entry points towards more sophisticated AI-driven adaptive learning systems that can personalise feedback, adjust difficulty levels, and provide predictive analytics on student performance. In the South African context, this technological integration occurs within a complex landscape characterised by significant infrastructure disparities, varying levels of digital literacy, and the accelerated digital transition necessitated by the COVID-19 pandemic. Understanding how gamified tools function

in these resource-variable environments provides critical insights for equitable implementation of technology-enhanced learning across diverse institutional contexts.

The theoretical foundation for gamified learning rests on several established educational frameworks. Self-Determination Theory (SDT) suggests that learning environments supporting autonomy, competence, and relatedness foster intrinsic motivation and deeper engagement (Ryan & Deci, 2000). Recent meta-analysis research confirms that gamification enhances student intrinsic motivation, perceptions of autonomy and relatedness, but has a minimal impact on competency (Sailer & Homner, 2020), suggesting that whilst motivational benefits are clear, careful design is required to ensure academic achievement. Cognitive Load Theory provides additional guidance, emphasising the importance of managing cognitive burden when introducing game elements to prevent interference with learning processes (Sweller, 1988). Active Learning Theory further supports gamification by advocating for student-centred approaches that promote knowledge construction through participation and interaction (Freeman *et al.,* 2014).

Digital quiz platforms such as Kahoot and Quizizz (now called Wayground) have emerged as accessible tools for implementing gamified learning in higher education. These platforms combine competitive elements, immediate feedback, and visual engagement to create interactive learning experiences that can transform passive lecture environments into dynamic, participatory spaces (Wang & Tahir, 2020). Their real-time analytics capabilities also provide educators with immediate insights into student understanding, enabling responsive teaching adjustments and formative assessment opportunities (Bicen & Kocakoyun, 2018).

Despite growing interest in gamified learning, significant gaps remain in understanding its specific impact within molecular biology education contexts. Limited research has examined how gamification affects student engagement with complex biochemical and molecular concepts, particularly at the upper undergraduate level, where content difficulty and academic

pressure are heightened. Furthermore, most existing studies focus on short-term engagement outcomes rather than sustained pedagogical transformation and student satisfaction over extended implementation periods.

This study addresses these gaps through three primary research objectives: 1. To evaluate the impact of Kahoot and Quizizz implementation on student engagement, motivation, and comprehension of complex Molecular Biology concepts at the third-year undergraduate level; 2. To identify student-perceived benefits and challenges associated with gamified assessment platforms in resource-variable learning environments; 3. To provide evidence-based recommendations for the sustainable integration of game-based learning tools in advanced STEM education. Through mixed-methods analysis, this study provides evidence-based insights into the effectiveness of gamification for addressing persistent engagement challenges in advanced STEM education, contributing to the broader Scholarship of Teaching and Learning (SoTL) discourse on innovative pedagogical practices in higher education.

## 2. Methodology

### 2.1. Participants and Context

This study involved students from the 2022 to 2024 cohorts enrolled in third-year Molecular Biology and/or Molecular Physiology modules at the University of Johannesburg. Over the three-year implementation period (2022-2024), approximately 200 students participated in the gamified learning activities across both modules, with the survey capturing responses from 27 participants (13.5% response rate). The participant demographic reflected the University's diverse student body, with them all being registered full-time undergraduate students in their third and final year of BSc degree programmes. While demographic data on gender, age, and prior academic performance were not systematically collected for this study, students came from varied socioeconomic backgrounds and had differing levels of prior exposure to digital learning tools.

Ethical clearance for this research was obtained from the University of Johannesburg Faculty of Science Research

Ethics Committee under reference number 2024-03-07/Allie. All participants provided informed consent prior to survey participation, and were assured of confidentiality, voluntary participation, and the right to withdraw at any time without academic penalty. Data were anonymised and stored securely in accordance with university research data management protocols. All participants provided informed consent prior to survey participation, and were assured of confidentiality, voluntary participation, and the right to withdraw at any time without academic penalty. Participation was on a voluntary basis.

## 2.2. Intervention

Gamified learning activities were integrated into third-year Molecular Biology and Molecular Physiology lectures using Kahoot (https://kahoot.com/) and Quizizz (now called Wayground, https://wayground.com/join/dashboard) platforms. These activities were administered to students at the end of relevant lectures to reinforce concepts and stimulate engagement.

## 2.3. Platform Selection and Rationale

Kahoot and Quizizz were selected based on several pedagogical and practical considerations aligned with the study's objectives and institutional context. Both platforms offer free educational tiers with intuitive interfaces requiring minimal technical expertise, making them suitable for diverse student populations with varying digital literacy levels. The platforms function across multiple devices (smartphones, tablets, laptops) and operate effectively even with moderate Internet bandwidth, a critical consideration within the South African higher education context where infrastructure access varies significantly.

Both tools support various question types (multiple-choice, true/false, short answer), enabling assessment of different cognitive levels from recall to application and analysis of molecular concepts. The platforms' immediate feedback mechanisms align with formative assessment principles essential for complex STEM learning. The comprehensive dashboard analytics provide real-time and post-session performance metrics, supporting data-driven pedagogical decisions and enabling identification of conceptual gaps requiring reinforcement.

Lastly, the integration of gamification elements (points, leaderboards, time pressure) combined with visual appeal was hypothesised to address the observed student passivity in traditional lecture formats, while the option for both individual and team-based participation accommodated different learning preferences.

## 2.4. Data Collection

Student perceptions and experiences regarding the gamified learning tools were captured through a comprehensive survey administered through Google Forms. This survey was shared with the student cohort following the implementation of Kahoot and Quizizz in lectures. The survey included a combination of quantitative and qualitative measures. Quantitative data were collected using Likert-scale statements, allowing students to rate their agreement with various aspects of the gamified activities on a five-point scale (Table 6.1). Qualitative data were gathered through open-ended questions, providing students an opportunity to articulate their personal experiences, insights, and suggestions regarding the use of Kahoot and Quizizz.

## 2.5. Data Reliability and Validity

Several measures were implemented to enhance the reliability and validity of data collection. Firstly, the Likert-scale statements and open-ended questions were developed based on established gamification and engagement literature (Sailer & Homner, 2020; Wang & Tahir, 2020), and reviewed by two faculty members with expertise in Science education research prior to administration.

The mixed-methods approach used for the study combined quantitative Likert-scale data with qualitative open-ended responses, enabling triangulation of findings, providing richer insights into student experiences beyond numerical ratings alone. This study did not include a comparison group of students who used traditional assessments without gamification, as all enrolled students participated in the gamified activities as part of their regular formative assessments. While this limits our ability to definitively attribute improvements solely to gamification, the consistent positive results across multiple student cohorts (2020-2024) and different course topics provide strong evidence

of effectiveness. Future studies could strengthen these findings by comparing matched groups of students using gamified versus traditional assessment methods

**Table 6.1:** Table outlining the types of questions and statements included in the Google Forms survey. The Likert-scale statements were designed to capture students' perceptions across various aspects of their experience with gamified learning, while open-ended questions provided qualitative insights.

| Question Type | Question/Statement (Likert Scale: 1=Strongly Disagree, 5=Strongly Agree) |
|---|---|
| **Quantitative** | Q1: The gamified learning tools (Kahoot/ Quizizz) made Molecular Biology concepts more engaging. |
| | Q2: I found the gamified learning sessions genuinely enjoyable. |
| | Q3: The gamified activities increased my motivation to engage with the course material. |
| | Q4: My comprehension of fundamental concepts improved through the use of these tools. |
| | Q5: The quizzes effectively reinforced my understanding of the module material. |
| | Q6: The platforms helped me identify areas requiring further study. |
| | Q7: I endorse the continued use of such platforms in future modules. |
| **Qualitative** | Please describe your overall experience using Kahoot and Quizizz in lectures. |
| | What did you find most beneficial about using these gamified tools? |
| | What challenges or difficulties did you encounter while using these tools? |
| | Do you have any suggestions for improving the use of gamified tools in future modules? |

## 3. Results and Discussion

The initial teaching approach for these complex modules relied heavily on traditional lecture formats utilising PowerPoint presentations, supplemented by visual aids and prescribed textbook readings. Whilst academically rigorous, this methodology inadvertently cultivated a predominantly passive learning environment. Students typically engaged with information passively and silently, deferring questions until after class, during one-on-one consultations, or avoiding them entirely. This passive reception limited opportunities for active cognitive processing, knowledge integration, and the construction of robust mental models necessary for understanding complex molecular mechanisms. Gauging real-time comprehension of complex concepts, such as genetic regulation pathways or physiological feedback mechanisms, proved consistently challenging. The inherent complexity of molecular-based content, combined with the intense pressure often found in university academic environments, particularly at the third-year exit level, exacerbated student anxiety. Many students, despite obvious intellectual capability, appeared paralysed by the prospect of being incorrect, resulting in less immediate participation, demotivation, and what we suspected was only superficial conceptual understanding. This issue is well-documented in higher education, where large class sizes and high-stakes assessments can deter active participation (Handelsman *et al.*, 2004). The aim of this study was to, therefore, critically examine the pedagogical transformation achieved through the integration of gamified learning platforms in advanced Molecular Biology and Molecular Physiology education, with particular focus on addressing student engagement challenges and enhancing learning outcomes in complex STEM content. Through systematic evaluation of Kahoot and Quizizz implementation across third-year modules, this research sought to provide evidence-based insights into the effectiveness of game-based learning tools in promoting active participation, improving conceptual understanding, and creating psychologically safe learning environments.

The findings from this mixed-methods investigation reveal that gamified platforms have fundamentally shifted student-educator interactions and learning processes. This discussion examines four key areas of transformative impact: active learning enhancement, immediate feedback mechanisms, visual learning integration, and peer learning facilitation. Additionally, the analysis explores the analytical capabilities of these platforms for data-driven pedagogical decision-making and presents student perceptions and feedback on the implementation and use of Kahoot and Quizizz. The implementation of Kahoot and Quizizz demonstrated several key benefits in the Molecular Biology and Molecular Physiology modules. These included the following:

1. The platforms successfully transformed passive learning into active engagement, particularly beneficial for complex molecular processes like signal transduction and gene regulation.
2. The real-time feedback allowed for prompt clarification of misconceptions, especially crucial in understanding sequential molecular events.
3. The visual elements in both platforms helped students to better grasp abstract molecular concepts and pathways.
4. Peer Learning Facilitation The competitive yet collaborative nature of these platforms fostered peer discussion and collective problem-solving.

One of the most valuable, yet often underutilised, features of Kahoot and Quizizz platforms lies in their comprehensive dashboard analytics and post-session reporting capabilities. These tools provide educators with immediate, actionable data that transforms gamified activities from simple engagement tools into sophisticated assessment instruments for both formative and summative evaluation purposes (Black & Wiliam, 2009; Nicol & Macfarlane-Dick, 2006).

The platform dashboards offer detailed performance metrics that extend far beyond traditional quiz scoring. As illustrated in the dashboard report summaries (Figure 6.1),

educators can access real-time data on student accuracy rates, completion percentages, participation levels, and question-specific performance patterns. For instance, the "Transcription in EK" quiz showed a 54% overall accuracy rate with 55 participants, while the "Endocrine system and Hormone action" quiz demonstrated 68% accuracy with 95% completion rate amongst 42 students. These metrics immediately highlight topics requiring additional reinforcement or alternative teaching approaches, supporting the principles of data-driven instruction (Marsh *et al.*, 2006).

The question-level analytics prove particularly valuable for identifying conceptual gaps and supporting evidence-based pedagogical decisions (Hattie & Timperley, 2007). When a quiz on "Signal Transduction Pathways" shows 58% accuracy with 100% completion amongst 32 students, it indicates that while students are engaged (high completion rate), the content complexity may require modified pedagogical strategies. This granular data enables educators to make evidence-based decisions about pacing, content reinforcement, and instructional modifications in real-time rather than waiting for traditional assessment results.

Furthermore, these platforms facilitate metacognitive development by allowing both students and educators to reflect on learning progress. The visual representation of performance data helps students to identify their knowledge gaps and areas of strength, promoting self-directed learning. For educators, the immediate feedback loop enables dynamic lesson adjustments, targeted review sessions, and personalised support for struggling students. The ability to track performance across multiple quiz iterations also provides longitudinal insights into student learning trajectories and concept mastery over time.

The reporting features also support collaborative learning environments by enabling peer comparison and group reflection. When students see that a complex topic like molecular transcription achieved only moderate accuracy rates across the entire class, it normalises learning challenges and encourages collective problem-solving rather than individual anxiety about comprehension difficulties.

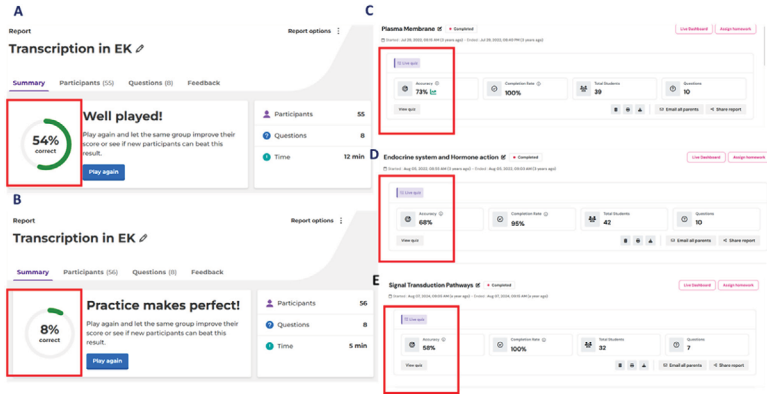



**Figure 6.1:** Representative dashboard reports from two Molecular Biology quiz sessions (A and B) and three Molecular Physiology (C-E) quiz sessions showing key performance metrics available to educators' post-implementation. Red boxes highlight critical performance indicators. Each dashboard provides immediate access to detailed analytics, including accuracy percentages, completion rates, total student participation, question counts, and time duration. These metrics enable educators to identify topics requiring additional reinforcement (lower accuracy rates) while maintaining high student engagement (high completion rates). Dashboard features facilitate data-driven pedagogical decisions, allowing for real-time instructional adjustments and targeted concept reinforcement based on student performance patterns.

## 3.1. Quantitative findings

The student survey results provided evidence of these tools' transformative impact, as summarised in Figure 6.2 with averages of above 4 for each of the questions Q1 to Q7. A striking 92.31% of students agreed or strongly agreed that Kahoot and Quizizz made Molecular Biology concepts significantly more engaging. This high level of engagement was further reflected in 96.15% of the students finding sessions genuinely enjoyable and 92.31% reporting increased motivation to engage with course material. These findings strongly corroborate the principles of Self-Determination Theory (Ryan & Deci, 2000), which suggests

that supporting psychological needs for autonomy, competence, and relatedness fosters intrinsic motivation. The competitive and interactive elements inherent in gamified platforms likely contributed to this heightened enjoyment and motivation, transforming a potentially intimidating subject into an inviting challenge (Sailer & Homner, 2020).

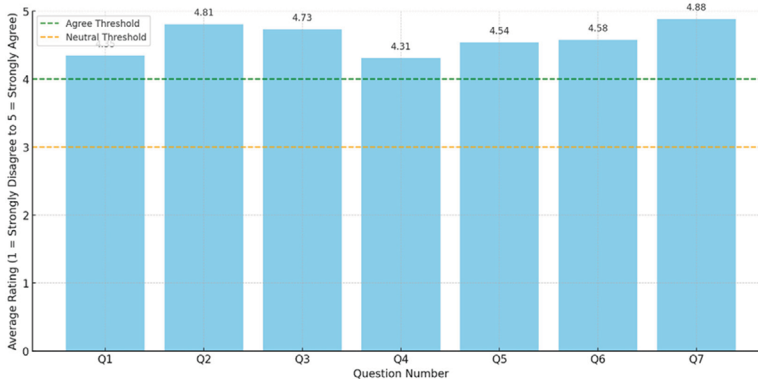



**Figure 6.2:** Student perceptions of gamified learning activities using Kahoot and Quizizz: Average ratings across eight survey statements. This bar graph summarises the average student ratings for seven Likert-scale statements evaluating their experiences with gamified learning tools (Kahoot and Quizizz) in a Molecular Biology and/or Molecular Physiology module. Responses were collected on a five-point scale, where 1 = Strongly Disagree and 5 = Strongly Agree. The green dashed line represents the "Agree" threshold (average = 4.0), and the orange dashed line marks the "Neutral" midpoint (average = 3.0). Most items were rated above the neutral threshold, indicating generally positive student perceptions of the gamified activities (n=27).

Beyond engagement, the tools demonstrated significant cognitive benefits. There were 88.46% of students who reported improved comprehension of fundamental concepts, with an equivalent percentage confirming that quizzes effectively reinforced module material understanding. Significantly, 88.46% agreed that the platforms helped them to identify areas requiring further study, showcasing the metacognitive benefits of real-time assessment.

This immediate feedback mechanism, a cornerstone of active learning (Freeman *et al.,* 2014), allows for iterative misconception correction and solidifies understanding of complex processes, as also supported by Diaz and Estoque-Loñez (2024) regarding enhanced student achievement. The unanimous support (100% of respondents) for the continued use of such platforms in future modules provides strong validation of their perceived value. Regarding platform preferences, 40.63% favoured Kahoot, 18.75% preferred Quizizz, and 21.88% appreciated both equally, suggesting that platform diversity effectively caters to varied learning preferences and learning styles.

## 3.2. Qualitative insights

The transformation in student engagement was evident not only in survey responses but also in observable classroom behaviours. Table 6.2 documents the key changes in student engagement patterns as observed by me across cohorts from 2018 to 2024 (pre- and post-COVID-19 pandemic), providing a behavioural foundation for understanding the student-reported experiences that follow.

**Table 6.2:** Observed changes in student engagement before and after gamification

| Engagement Indicator | Before Gamification (2018–2019) | After Gamification (2020–2024) |
|---|---|---|
| **Voluntary Participation** | Rare; students reluctant to speak or answer questions | High; active competition to answer, visible enthusiasm |
| **Question-Asking Behaviour** | Questions deferred to after class, office hours, or avoided entirely | Real-time questioning during quiz feedback sessions |
| **Classroom Energy** | Passive, quiet reception of content | Animated, vocal, energetic engagement |

(*Continued*)

**Table 6.2:** Observed changes in student engagement before and after gamification (*Continued*)

| Engagement Indicator | Before Gamification (2018–2019) | After Gamification (2020–2024) |
|---|---|---|
| **Peer Discussion** | Minimal interaction; students worked silently | Spontaneous discussion of concepts, peer learning |
| **Attendance Patterns** | Declining through the semester | Sustained; students anticipated quizzes at the lecture end |
| **Risk-Taking Behaviour** | Visible hesitation; fear of being incorrect | Reduced anxiety; anonymity fostered willingness to attempt answers |
| **Student Attitude** | Compliance-based; obligation to attend | Intrinsic interest; enjoyment of learning process |
| **Engagement Timing** | Focus wanes after 30–40 minutes | Sustained attention through entire session |
| **Anxiety Indicators** | Visible hesitation; fear of judgement | Reduced; anonymity fostered risk-taking |

*Note:* This table is based on instructor observations and teaching reflections documented across multiple cohorts. While qualitative, these patterns were consistent and observable across both Molecular Biology and Molecular Physiology modules.

These observable behavioural shifts closely align with students' self-reported experiences, as captured in open-ended survey responses. The analysis of the open-ended responses from the student survey provided rich qualitative insights, revealing three dominant themes that further characterise the student experience and align with the behavioural changes documented in Table 6.2.

Theme 1: Enhanced Engagement Through Playful Learning

Firstly, students consistently emphasised enhanced engagement through playful learning. Responses highlighted the fun, interactive, and competitive nature of the gamified tools as

primary drivers for their involvement. For example, students noted how "*The quizzes were fun and time-based, they turned studying into a game!*" or that the "*competitive aspect of Kahoot... made learning more engaging*." These student descriptions directly reflect the behavioural changes shown in Table 6.2, particularly the shift from passive reception to active competition and the transformation of attendance from obligation to anticipation. The student descriptions of "time-based" challenges that "turned studying into a game" suggest experiences consistent with Csikszentmihalyi's (1990) Flow Theory, where optimal engagement occurs when task difficulty matches skill level while providing clear goals and immediate feedback. However, the tension that some students expressed between "focusing on the game" versus "the knowledge and information to be gained" highlights the delicate balance required in gamification design - challenges must be sufficiently demanding to maintain flow states without creating cognitive overload that displaces learning objectives (Sweller, 1988). These views align with research on gamification's effectiveness in educational contexts (Wang & Tahir 2020, Fitriyani, 2025), highlighting how competitive elements and interactive design can foster positive emotional engagement while simultaneously reducing traditional academic anxiety, thereby creating a healthy learning environment.

Theme 2: Conceptual Clarification Through Immediate Feedback

Secondly, conceptual clarification through immediate feedback was highly valued by the students. Students particularly appreciated the real-time feedback mechanisms for elucidating complex concepts and reinforcing understanding. Feedback such as "*Kahoot's answer reviews helped me realise why I mixed up transcription/translation enzymes*," and "*It helped me understand some of the confusing work that we did in 3A, it helped with operons and Ek transcription and transla*tion..." highlights the pedagogical value of immediate feedback. This theme relates to the "question-asking behaviour" change documented in Table 6.2, where students shifted from avoiding questions to engaging with real-time questioning during feedback sessions. This aligns with active learning theory (Freeman *et al.,* 2014), facilitating iterative misconception correction and solidifying the comprehension of fundamental molecular processes.

Theme 3: Technical and Design Barriers

Finally, while feedback was primarily positive, students also articulated practical challenges, categorised as technical and design barriers. Some of the common concerns included technological infrastructure, such as "*Slow Wi-Fi meant I lost points, which is frustrating when you know the answer*!" Additionally, issues related to question design and timing were raised, with one student noting, "*The main difficulty was that the Kahoot tool had a short time frame to respond. I started focusing on the game and not always the knowledge and information to be gained.*" These comments highlight the importance of optimally balancing competitive elements with adequate cognitive processing time, particularly for complex molecular concepts, a consideration that aligns with Cognitive Load Theory principles (Sweller, 1988; Cox & Williams, 2008) to prevent cognitive overload.

## 3.3. Personal reflections

Beyond the quantitative metrics and analytical insights, a deeper understanding of the pedagogical transformation occurred through qualitative reflections and anecdotal evidence from the lectures for these modules. Students consistently expressed genuine enjoyment and enthusiasm for the gamified quizzes, frequently describing the sessions as "fun" and "interactive". This shift transformed the perception of learning challenging molecular concepts, with students noting how the quizzes "*turned studying into a game!*". The competitive aspect, while managing to prevent cognitive overload, was particularly highlighted as a driver for engagement and motivation, making learning more stimulating. Anecdotal observations further solidified this, revealing a palpable increase in student energy and vocal participation before and during these gamified activities. This intrinsic motivation, supported by the platforms' ability to foster autonomy, competence, and relatedness, contributed to students actively looking forward to the quizzes at the end of lectures, transforming a potentially intimidating assessment into an anticipated and enjoyable part of their learning journey. This positive anticipation highlights how the gamified approach successfully created a psychologically safe environment where students felt empowered to engage without the fear of judgment.

## 4. Limitations and Future recommendations

The integration of gamified learning tools has transformed the educational experience within these Molecular Biology and Molecular Physiology modules. While the high rates of confirmed enhanced engagement are significant, qualitative feedback suggests that continuous refinement is required to optimally balance competitive elements with adequate cognitive processing time. This pedagogical approach's effectiveness is strongly validated by the consistently high satisfaction scores and unanimous call for its continued use. Student improvement suggestions, including requests for increased visual content and enhanced question complexity, directly support Cognitive Load Theory applications by diversifying content formats to accommodate varied learning styles whilst deepening cognitive processing requirements.

This study has several limitations that warrant attention. This study did not include a comparison group of students who used traditional assessments without gamification, as all enrolled students participated in the gamified activities as part of their regular coursework. While this limits our ability to definitively attribute improvements solely to gamification, the consistent positive results across multiple student cohorts (2020-2024) and different module topics provide strong evidence of effectiveness. Future studies could strengthen these findings by comparing matched groups of students using gamified versus traditional assessment methods. Long-term knowledge retention beyond immediate lecture settings requires further investigation. Furthermore, challenges such as technology-accessibility concerns and the time investment required for creating quality questions remain pertinent. As educators, we must also be mindful of the potential for surface-level learning if activities are not properly designed, therefore, emphasising conceptual understanding over simple recall.

While Kahoot and Quizizz offer free educational tiers, scaling gamified assessments across entire departments or institutions raises sustainability questions. The time investment required to create high-quality, conceptually focused questions is substantial; effective quiz design demands disciplinary expertise,

pedagogical knowledge, and familiarity with the technical platform. Institutions seeking widespread adoption must consider faculty training programmes, dedicated instructional design support, and perhaps recognition of this work within workload models and promotion criteria.

Based on these insights, several practical implications and recommendations have emerged for effective implementation. These include the strategic timing of game-based activities (e.g., at the end of lectures for reinforcement), careful question design focusing on conceptual understanding, and seamless integration with traditional teaching methods. Educators should also regularly collect feedback and adapt their approach. Specific recommendations for content design include beginning with simple concepts before progressing to complex molecular pathways, using visual elements to illustrate molecular processes, and incorporating both individual and team-based activities to cater to the diverse learning needs of the students. Regular assessment of learning analytics is also crucial to adjust teaching strategies dynamically.

From an international perspective, challenges surrounding student engagement and complex content mastery remain universal educational concerns. The fundamental principles underlying gamification, active learning promotion, and immediate feedback provision demonstrate significant transferability across diverse educational contexts. While resource availability may vary globally, the core concept of rendering learning interactive and less intimidating holds considerable potential for enhancing educational outcomes universally. This study highlights UJ's commitment to "showcasing innovative teaching and learning projects" whilst promoting inclusive pedagogical practices that inspire minds and shape futures.

## 5. Conclusion

In conclusion, the integration of Kahoot and Quizizz (Wayground) into Molecular Biology and Molecular Physiology modules has proven transformative. The empirical data from this study confirm that these gamified tools significantly enhanced student engagement, promoted more enjoyable learning experiences,

and effectively clarified complex concepts, converting passive knowledge recipients into active, confident, and enthusiastic learners. By establishing psychologically safe and enjoyable learning environments, these tools empowered students to overcome participation fears, a challenge particularly amplified during online learning's "black screen" era. This study provides evidence-based support for the strategic implementation of game-based learning platforms in upper-level science modules and emphasises the Scholarship of Teaching and Learning's (SoTL) impact in the development of inclusive, dynamic educational practices that genuinely embody UJ's ongoing legacy. As educators, our commitment must remain focused on continuously evolving pedagogical approaches, prioritising the student voice and active participation to unlock learners' full academic potential. The evidence presented here suggests that thoughtfully implemented gamification strategies represent not only technological innovation but fundamental pedagogical transformation that can bridge the gap between complex content and student comprehension.

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Chapter 7

# V-Labs: Transforming Traditional Scientific Experimentation for Students into Meaningful Experiences

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## Abstract

In higher education, experiential learning plays a vital role in every discipline of Science. A typical graduate should be able to collect and analyse qualitative and quantitative data and use scientific enquiry to solve real-world problems. To achieve this, students must be exposed to laboratory activities enabling the development of hands-on skills and critical thinking. Traditionally, laboratory sessions are held physically despite requiring expensive infrastructure and being labour- and time-intensive. Consequently, many of the learners from schools in under-resourced countries like South Africa have limited or no accessibility to well-equipped laboratories, making it difficult for them to learn laboratory-based subjects

such as Life and Physical Sciences when they enter university. Many of these students enter higher education with nearly zero prior laboratory experience because of the systemic experiential gap in under-resourced schooling. This lack of exposure is not merely a logistical hurdle; it is a significant psychological barrier that manifests as "apprehension and confusion" once students are in a tertiary laboratory setting. In this context, Virtual laboratories (V-Labs) serve as more than just a "tech tool"; they act as a levelling mechanism. By providing the "missing" foundational exposure in a safe, digital space, V-Labs allow students to build confidence and basic procedural knowledge before they ever step into a physical laboratory.

Building on this need for a levelling mechanism, V-Labs and online simulations are digital tools that are increasingly used in pedagogical practice to mitigate the challenges of excessive cost and insufficient equipment and infrastructure, especially in developing countries. V-Labs and simulations are digital versions of experiments or hands-on activities that allow students to interactively explore scientific concepts in a virtual environment. The reviewed literature highlights multiple benefits of V-Labs including flexible, self-paced, and fear-free learning in a safe environment. This chapter presents a narrative review of V-Labs and simulations as emerging digital technologies used in higher education. It further describes the use of V-Labs to familiarise undergraduate students in Science disciplines with the experimental set-up and protocol of experimental activities prior to physically conducting the experiment in the laboratory. The candidates were exposed to V-Labs as a pre-practical exercise followed by performing the experiment in the physical laboratory. Whilst there are overwhelming empirical reports on V-Labs contributing positively to achieving experiential learning goals, student experiences and perspectives are usually omitted. To address this gap, this chapter gives specific attention to the "student voice" by referring to student questionnaires and feedback exercises that were used to share insights and opinions on the pedagogical practice of using digital tools to enhance their experiential learning.

**Keywords:** Digital education; Experiential learning; Laboratory training; Student experience

## 1. Introduction and Background

The persistent challenges in scientific education, particularly within under-resourced educational contexts, necessitate the urgent development and implementation of innovative pedagogical approaches to practical learning. The foundational role of laboratory work in developing critical scientific skills, developing conceptual understanding, and cultivating an authentic appreciation for scientific enquiry is clearly acknowledged across all Science, Technology, Engineering and Mathematics (STEM) disciplines (National Research Council, 2005; Hofstein & Lunetta, 2004). However, recent educational research, including comprehensive systematic reviews by Raman *et al.,* (2022) and Sellberg *et al.,* (2024), highlights significant and ongoing barriers to effective scientific training, especially in disciplines that require complex, hands-on practical skills, such as Microbiology and Biochemistry. These barriers are not only logistical; they also impact student engagement, confidence, and ultimately, their long-term success in scientific fields.

The growing landscape of digital learning technologies offers promising avenues to mitigate these challenges. A recent systematic review of virtual laboratories in STEM higher education by Sellberg *et al.,* (2024) provides critical and timely insights into the current state of these digital learning technologies, their efficacy, and their evolving pedagogical applications. This contemporary analysis, complementing the historical and foundational perspectives offered by Raman *et al.*, (2022) on the evolution of laboratory instruction, collectively emphasises the growing and indispensable importance of virtual laboratory environments in addressing multifaceted educational challenges. These reviews establish a robust evidence base for the potential of virtual laboratories to democratise access to high-quality scientific education.

To explain how digital tools help students to learn practical skills, this study used Kolb's Experiential Learning

Cycle as a guide (Kolb, 1984). V-Labs facilitate the "Reflective Observation" and "Abstract Conceptualization" phases by allowing students to visualise molecular processes that are otherwise invisible in a wet-lab. Furthermore, the constructivist nature of these simulations allows students to "make mistakes" and repeat procedures without the penalty of resource wastage. This builds the cognitive scaffolding necessary to bridge the systemic experiential gap, preparing students for the "Active Experimentation" phase in the physical laboratory.

Traditional laboratory-based learning, while invaluable, inherently encounters a multitude of constraints that disproportionately affect institutions with limited resources. These widely recognised limitations include:

- **Prohibitive infrastructure costs:** The capital outlay for constructing and maintaining state-of-the-art laboratory facilities, full of specialised ventilation systems, safety protocols, and dedicated space, is often beyond the reach of many educational institutions, particularly in developing economies (Shewbridge *et al.*, 2016).
- **Limited access to specialised equipment:** Beyond infrastructure, the acquisition, maintenance, and regular calibration of sophisticated scientific equipment (for example spectrophotometers, polymerase chain reaction (PCR) machines, advanced microscopes) represent significant ongoing expenditures, restricting the scope and depth of practical experiences that can be offered.
- **Time-intensive practical sessions and curriculum constraints:** Traditional practical sessions often demand significant blocks of time for set-up, execution, and clean-up, making integration into already dense curricula challenging and limiting the frequency of hands-on experiences (Akuma & Gaigher, 2023).
- **Restricted accessibility and inclusivity:** The physical presence required for traditional laboratories, coupled with potential travel costs and the need for specific personal protective equipment, can create substantial barriers for students from economically disadvantaged backgrounds, those with disabilities, or those balancing work and study commitments.

These systemic limitations are particularly pronounced and impactful in developing countries like South Africa, where educational institutions frequently grapple with severe resource scarcity and historical disparities in educational provision (Department of Higher Education and Training (DHET), 2019). Consequently, students entering tertiary education, especially in Science-intensive fields, often face significant and cumulative challenges because of their limited prior practical exposure. This shortage manifests in several critical ways: increased anxiety in novel laboratory environments, reduced confidence in their ability to apply scientific methodologies, potential disengagement from challenging scientific disciplines because of perceived barriers, and, crucially, compromised development of fundamental practical scientific techniques. This systemic educational shortfall creates a critical and universal barrier that prevents many talented students from fully engaging with, excelling in, and ultimately pursuing careers in STEM fields, thereby hampering their academic progression and professional potential in scientific domains. This chapter addresses a specific teaching and learning gap: the "experiential gap" often found in under-resourced STEM environments. While advanced digital twin technologies exist, this work explores how accessible, Web-based V-Labs can specifically bridge the transition from high school to university-level Biochemistry. By providing a digital "familiarisation layer," this intervention seeks to extend the traditional laboratory model by ensuring that students do not use their limited physical lab time merely to overcome initial anxiety, but to engage in high-level scientific enquiry.

In response to these educational challenges, V-Labs have emerged as a transformative technological solution. Drawing deeply from the insightful analyses provided by Raman *et al.,* (2022) and Sellberg *et al.,* (2024), these digital simulation platforms offer a compelling array of significant advantages that directly address the limitations of traditional practical instruction:

1. V-Labs significantly reduce or eliminate the need for expensive physical infrastructure, consumables, and specialised equipment, making high-quality practical experiences accessible to a broader range of institutions (Rutten *et al.,* 2012).

2. Digital environments allow for the precise control of variables, ensuring that every student experiences the same experimental conditions, which facilitates reproducibility, consistent learning outcomes, and effective assessment (Santos & Prudente, 2022).
3. Students can repeat experiments numerous times without concern for material wastage, equipment breakage, or time limitations, promoting mastery through repeated practice and iterative learning.
4. V-Labs eliminate exposure to hazardous chemicals, biological agents, or dangerous equipment, providing a safe space for experimentation, particularly crucial in disciplines like Microbiology.
5. Students can progress through experiments at their own pace, pause and review concepts, and engage with interactive elements that adapt to their learning needs, promoting deeper understanding and engagement (Sitzmann, 2011).

Despite these substantial potential benefits, a significant and persistent research gap remains concerning the nuanced qualitative aspects of student experiences and perceptions within these digital learning environments. While Kerr *et al.,*'s early work (2004) already suggested the innovative and disruptive potential of virtual laboratories, and Sellberg *et al.,* (2024) have confirmed their continued relevance and growing adoption, there is a critical need for deeper qualitative and mixed-methods research that moves beyond mere efficacy comparisons to truly understand the lived experiences, psychological impacts, and pedagogical implications of V-Labs from the student's perspective. Understanding these nuances is crucial for optimising the design and implementation of V-Labs to ensure that they genuinely enhance, rather than merely replicate, traditional learning.

This research aimed to directly address these identified gaps by:

1. Systematically exploring and describing student experiences with virtual laboratory environments, focusing on their perceptions of engagement, utility, usability, and affective responses.

2. Investigating the pedagogical impacts of digital experimental simulations, including their influence on student confidence, anxiety levels, motivation, and the development of core scientific process skills.

The proposed investigation is particularly timely and relevant, given the recent systematic reviews by Raman *et al.,* (2022) and Sellberg *et al.,* (2024), which collectively emphasise the evolving and increasingly central role of virtual laboratories in contemporary educational practices globally. By rigorously capturing student opinions, meticulously analysing their diverse experiences, and evaluating specific learning outcomes, this study aimed to contribute robust, data-supported insights into innovative scientific education methodologies. The focus was on Microbiology and Biochemistry-specific modules offered at the University of Johannesburg (UJ), thereby providing contextually relevant findings for resource-constrained environments.

## Research Questions

1. How do students perceive their engagement, learning, and overall experience with virtual laboratory environments in Microbiology and Biochemistry modules?
2. What are the comparative learning outcomes (e.g., conceptual understanding, procedural knowledge, practical skill application) between students primarily utilising traditional laboratory approaches and those engaging with virtual laboratory simulations?
3. How do digital tools, specifically virtual laboratories, enhance or transform experiential learning processes in scientific education, particularly in relation to student confidence, anxiety, and self-efficacy?

This research has the potential to significantly advance the careful and effective integration of educational technology by providing evidence-based insights into optimal digital learning strategies for Practical Science. The study aimed to directly inform and support curriculum development in resource-constrained environments, offering practical, scalable, and effective approaches to enhancing scientific education

through innovative technological interventions. By investigating student experiences with virtual laboratories, the research will contribute invaluable perspectives to ongoing discussions on inclusive scientific education, particularly in contexts where traditional laboratory access is severely limited or inequitable. In conclusion, the findings generated from this study will provide a nuanced and empirically grounded understanding of precisely how digital tools can effectively bridge educational gaps, substantially improve learning outcomes, and ultimately create more equitable and accessible pathways to high-quality scientific training across diverse and challenging educational settings.

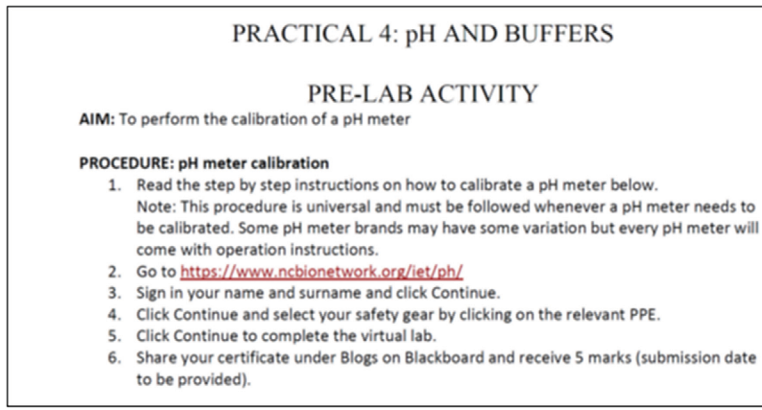
## 2. Research Methodology

### 2.1. Module

The module Biochemistry 2 (Module code: BIC12B1) was used to pilot the incorporation of V-Labs into the practical component of the course material from 2022 to 2024. The module is offered to second-year students enrolled for the Diploma in Biotechnology at the University of Johannesburg. This qualification is a four-year extended curriculum programme (ECP) which is similar in structure to Foundation-year programmes available in the UK. The purpose of the module is to introduce students to the general principles of Biochemistry with the emphasis on the major classes of biological molecules. Practical application is emphasised, and the student is required to demonstrate understanding of biochemical principles by performing procedures and operating equipment in a basic Biochemistry laboratory.

### 2.2. Mode of Delivery

V-Labs were presented as either simulations (for training students on common equipment used in the laboratory) and videos sourced from YouTube or *Journal of Visualized Experiment (JoVE)* to familiarise the students with the experimental method. Figures 7.1 to 7.3 are examples of V-Lab activities taken from the practical guides provided to students via the online learning management system (LMS) Moodle.



PRACTICAL 4: pH AND BUFFERS

PRE-LAB ACTIVITY

**AIM:** To perform the calibration of a pH meter

**PROCEDURE: pH meter calibration**

1. Read the step by step instructions on how to calibrate a pH meter below.
   Note: This procedure is universal and must be followed whenever a pH meter needs to be calibrated. Some pH meter brands may have some variation but every pH meter will come with operation instructions.
2. Go to https://www.ncbionetwork.org/iet/ph/
3. Sign in your name and surname and click Continue.
4. Click Continue and select your safety gear by clicking on the relevant PPE.
5. Click Continue to complete the virtual lab.
6. Share your certificate under Blogs on Blackboard and receive 5 marks (submission date to be provided).

**Figure 7.1:** Snapshot of a pre-laboratory activity where the simulation was used to prepare students on the method of how to calibrate a pH meter. This pre-lab simulation reduces procedural anxiety by allowing students to master the calibration steps virtually before handling physical equipment.

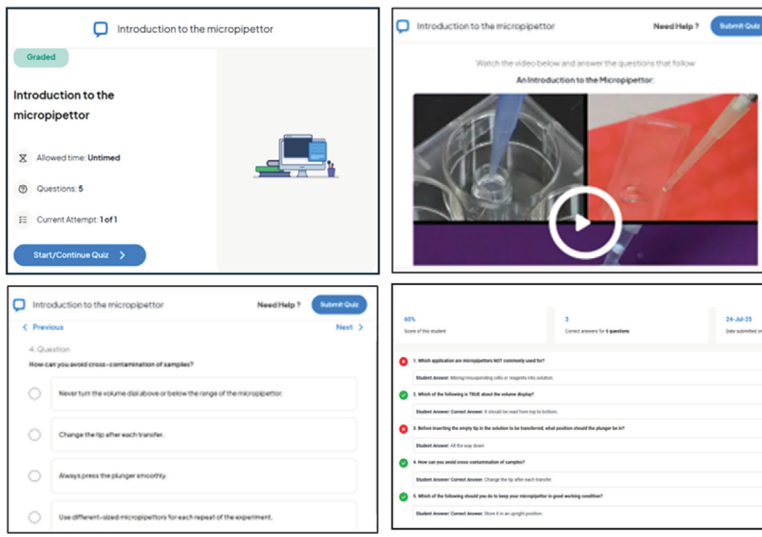
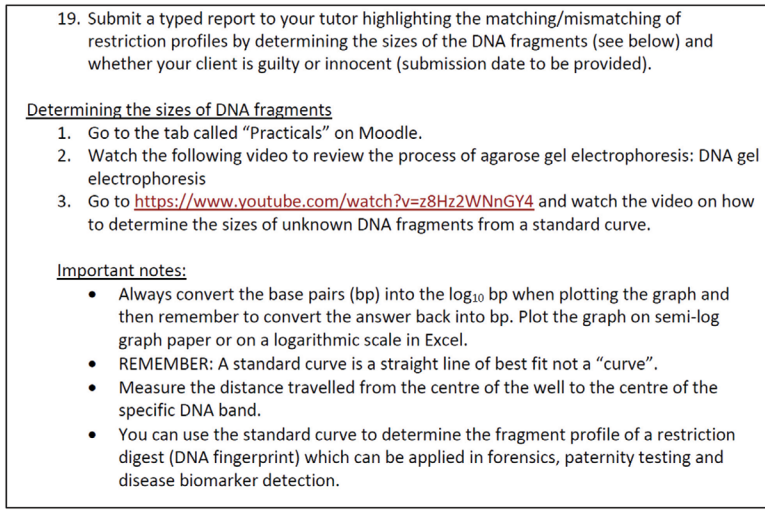



**Figure 7.2:** Snapshot of a learning activity where students were required to watch a video prior to the wet-lab and complete a short quiz. This functions as a formative assessment to ensure that students grasp basic mechanics and safety protocols, thereby protecting expensive reagents in the wet-lab.



19. Submit a typed report to your tutor highlighting the matching/mismatching of restriction profiles by determining the sizes of the DNA fragments (see below) and whether your client is guilty or innocent (submission date to be provided).

Determining the sizes of DNA fragments

1. Go to the tab called "Practicals" on Moodle.
2. Watch the following video to review the process of agarose gel electrophoresis: DNA gel electrophoresis
3. Go to https://www.youtube.com/watch?v=z8Hz2WNnGY4 and watch the video on how to determine the sizes of unknown DNA fragments from a standard curve.

Important notes:

- Always convert the base pairs (bp) into the $\log_{10}$ bp when plotting the graph and then remember to convert the answer back into bp. Plot the graph on semi-log graph paper or on a logarithmic scale in Excel.
- REMEMBER: A standard curve is a straight line of best fit not a "curve".
- Measure the distance travelled from the centre of the well to the centre of the specific DNA band.
- You can use the standard curve to determine the fragment profile of a restriction digest (DNA fingerprint) which can be applied in forensics, paternity testing and disease biomarker detection.

**Figure 7.3:** Snapshot of an activity where students were required to watch a video showing them how to process their data for inclusion in a written report that served as part of the formative assessment in the module. This supports "Reflective Observation" by helping students to visualise and interpret raw data into a structured scientific report.

Students were tasked to engage with V-Labs either before or after the hands-on practical. The purpose of exposing students to the simulations and videos as a pre-laboratory activity was to introduce the topic and principle of the experiment, show them the type of equipment that will be used and demonstrate the experimental set-up that they would see in the laboratory. Alternatively, students were encouraged to redo the simulations and watch the videos whilst preparing their written experimental report as a reminder of what they had already performed in the hands-on practical.

## 3. Results and Discussion

A Google survey (Ethics reference number: 2025-05-06/ Kondiah, Appendix I) consisting of twenty-eight questions was electronically disseminated to students who had completed any of the V-Labs activities, to evaluate their views and opinions of their experience. The survey was based on a Likert scale ranging

from 1 to 5, where a score of 1 represented "strongly disagree" to a score of 5, which represented "strongly agree" as a response to a question. The survey covered four sections: learning experience, overall satisfaction, open-ended questions and demographic information. The complete Google survey can be found as Appendix II and was entirely voluntary. In addition, student feedback was also received via a "Start, Stop, Continue" method.

The purpose of receiving student feedback was to (i) compare their experiences between traditional hands-on laboratories and V-Lab simulations and (ii) reflect on whether V-Labs are an effective pedagogical tool to deliver learning outcomes in practical disciplines such as Biochemistry and Microbiology. Key aspects of the evaluation included:

- Assessment of the effectiveness of V-Labs in teaching practical laboratory skills.
- Gauging student perceptions and experiences with the V-Lab environment.
- Develop evidence-based recommendations for integrating technology into Microbiology and Biochemistry education.

## 3.1. Findings

A total of 16 students (out of 150, 10.6%) volunteered to participate in the Google survey. All students were in their second year of study and indicated that they had some prior laboratory experience in Biology / Biochemistry or Microbiology. The findings from the survey are presented as three separate sections: learning experience, overall satisfaction and open-ended feedback.

*Learning experience*

Six questions related to the students' learning experience were included in the survey. The questions were answered based on a Likert scale that best represented the student's level of agreement with the statements provided. A graphical overview of the student responses to the six statements can be seen in Figure 7.4.

A total of 80% of the respondents strongly appreciated that V-Labs offered them the opportunity to repeat the experiments multiple times compared to the wet-lab experience. Two other

areas where the majority of the respondents strongly agreed with the statements provided were that the V-Labs were intuitive and easy to navigate (53.3%) and provided helpful feedback on their technique and approach to the practical activity (46.7%). While an equal number of respondents agreed or strongly agreed that virtual simulations accurately represent real-world experiences in Biochemistry or Microbiology, one student disagreed with the statement. Similarly, the majority of the respondents felt that the V-Lab experience prepared them well for the wet-lab experience, except for one respondent who disagreed. A total of 53.3% of the participants confirmed that they did not experience technical difficulties whilst conducting the V-Labs. However, 40% remained neutral and 6.7% (1 student) seems to have undergone a negative experience with technology.

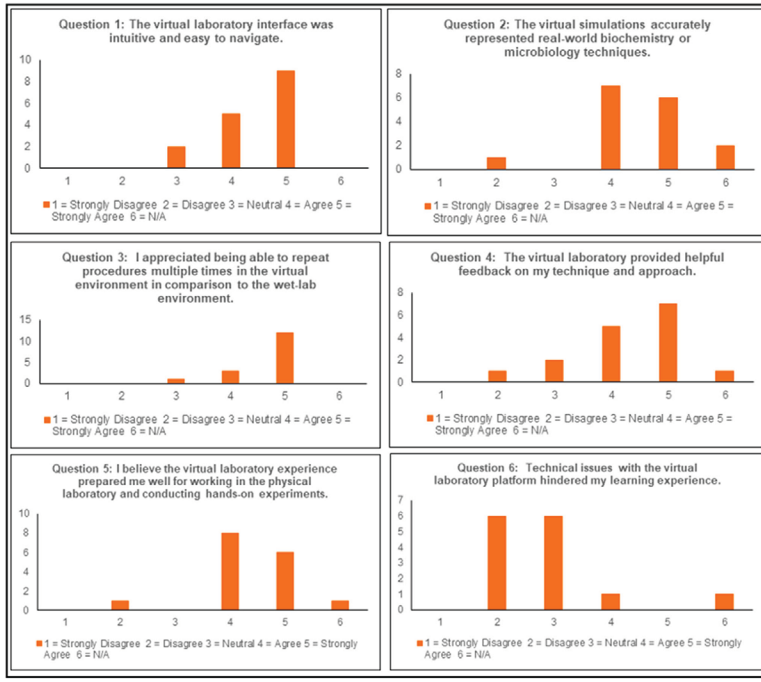



**Figure 7.4:** Graphical presentation of the responses received from the Google survey (Appendix II) that covers the aspect of the student learning experience with V-Labs.

## Overall satisfaction

To determine the students' overall satisfaction with the inclusion of V-Labs into their practical curriculum, four questions were posed to them. The respondents once again used a similar Likert scale to that of the learning experience and the outcome is presented as Figure 7.5. The general overall observation was that respondents were agreeable that V-Labs met their laboratory expectations as well as prepared them for future coursework in the discipline. Although 73.3% (11) of the respondents would recommend the use of a combination of V-Labs and hands-on activities for the practical component of a module, 20% (3) remained neutral in their view.

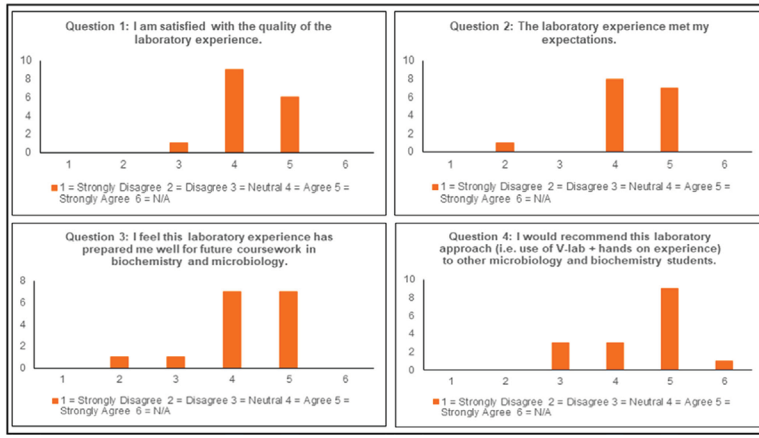



**Figure 7.5:** Graphical presentation of the responses received from the Google survey (Appendix II) that covers the aspect of the students' overall satisfaction with V-Labs.

## Open-ended feedback

The third section of the Google survey consisted of four open-ended questions. These questions enabled respondents to expand on perspectives gained from their experience of V-Labs and are summarised in Table 7.1.

**Table 7.1:** Main themes that were identified from the responses received to four open-ended questions on the V-Lab student experience.

| Question | Identified themes |
|---|---|
| What aspects of the laboratory experience did you find most valuable for your learning? | • Enabled familiarity with instruments and reagents prior to the wet-lab.<br>• Visual aid for following the experimental steps.<br>• Flexibility to repeat the experiment and make mistakes. |
| What challenges, if any, did you encounter during the laboratory experience, and how did you overcome them? | • Technical challenges e.g. not user-friendly on phones, lags caused by overburdening of the system etc.<br>• Does not teach you how to deal with experimental errors such as procedural or instrumental errors. |
| How could the laboratory experience be improved to facilitate your learning better? | • Improving the user interface.<br>• Arrange training / demo on how to navigate V-Labs.<br>• Make the simulations more realistic.<br>• Include voice-overs to explain the V-Labs.<br>• Include explanations on the principles of the instruments and reagents used.<br>• Add in troubleshooting of possible experimental errors. |
| What specific features of the virtual laboratory did you find most helpful for learning Microbiology and/or Biochemistry techniques? | • Visual aids and animation.<br>• V-Labs were interactive and self-paced.<br>• Step-by-step tutorials |

### Start-Stop-Continue exercise

Once the laboratory activities were completed, the students taking the module Biochemistry 2 were asked to participate in a Start-Stop-Continue exercise to gain rapid feedback for reflection and improvement of the laboratory learning experience. The exercise was completely anonymous and voluntary. Figure 7.6 is a snapshot of the responses that were received. All responses indicated that V-Labs should be continued; none of the responses mentioned that the virtual experience should be stopped.

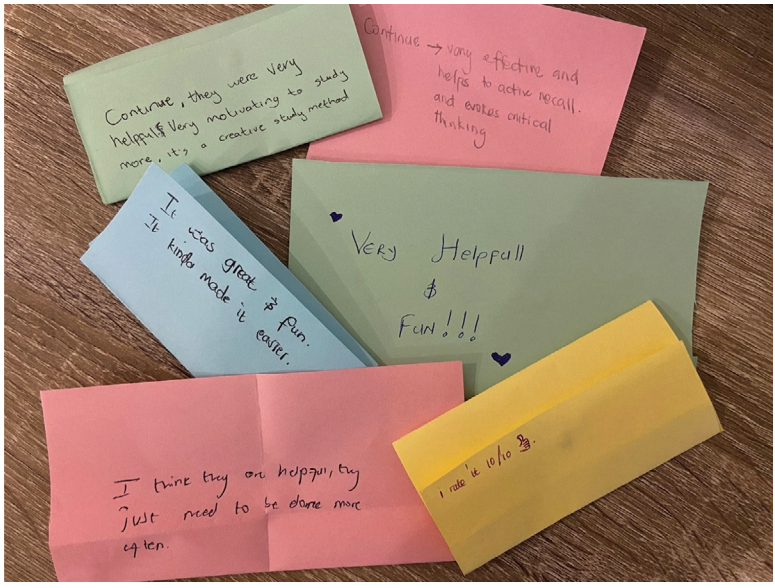



**Figure 7.6:** Responses received during a Start-Stop-Continue activity based on the students' experience with V-Labs.

## 3.2. Discussion

In the discipline of Science, experiential learning almost always takes on the form of laboratory-based training. Students are required to follow specific protocols to perform experiments, generate and analyse data outputs and report on their findings. This process leads to skills development in terms of technical capabilities, critical thinking, problem-solving, analytical skills

and scientific communication. In under-resourced countries such as South Africa, the rising need for higher education institutions to provide the necessary facilities in terms of infrastructure, equipment and access to conduct laboratory-based training poses a risk to students who want to study Life or Physical Sciences. As more and more students find themselves pursuing higher degrees in Science, such resources become increasingly limited.

The advancement of technology and subsequent availability of digital tools for use in education is gaining the attention of educators worldwide. V-Labs and online simulations of experiments are an exciting alternative to the pedagogical practice of wet-lab learning. These digital resources are interactive, exploratory and provide flexible, self-paced, fear-free learning opportunities. There is overwhelming empirical evidence in the reviewed literature that shows how V-Labs are contributing positively to achieving experiential learning goals. However, we have found that oftentimes the student experience and perspectives are missing from these reports. The study that we report on here attempts to include the student voice as part of the growing evidence in support of digital learning experiences with a directed focus on experiential learning in the discipline of Biochemistry and Microbiology.

The findings described were based on both qualitative and quantitative data obtained from second-year students in the Faculty of Science at the University of Johannesburg who had participated in the V-Lab experience as part of their laboratory training. To ascertain their perspective and provide them with a platform for feedback, a Google survey and Start-Stop-Continue exercise was conducted.

The results of this survey provide empirical evidence that V-Labs serve as a vital levelling mechanism, directly addressing the "paucity of prior exposure" typical in under-resourced secondary education. By moving through the "Reflective Observation" and "Abstract Conceptualization" phases defined by Kolb (1984) in a virtual space, students in this pilot were able to transform their systemic experiential gap into a state of digital familiarity. This shift reduced the cognitive load and psychological apprehension identified in the introduction of this chapter.

Furthermore, the high satisfaction rate regarding the ability to "repeat experiments" confirms that the constructivist nature of V-Labs allows for a safer, more iterative mastery of procedures. This mastery acts as a pedagogical bridge: by the time that students reach the "Active Experimentation" phase in the physical wet-lab, they are performing with confidence rather than confusion. This confirms that digital twins are not merely technical substitutes but are essential tools for fostering meaningful scientific enquiry in the South African context.

However, successfully scaling these "digital twins" requires careful consideration of digital equity and ethics. As noted in the student feedback regarding technical lags and mobile compatibility, the "experiential gap" is often compounded by a "digital divide" in hardware and data access. To implement these tools responsibly in low-resource contexts, institutions must prioritise low-bandwidth simulations and zero-rated data access. This ensures that V-Labs function as an inclusive pathway to Science rather than a new barrier for students with limited technological resources.

One of the major limitations of this study was that only 16 out of over 150 students responded to the call for feedback. While this was a low response rate, it did not diminish from exploring and describing student experiences with V-Lab environments, in the context of their perceptions of engagement, utility, usability and affectivity.

## Acknowledgements

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# Chapter 8

# Breaking the Educational Barrier – Virtual Reality in Chemical Education

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## Abstract

Education in Chemistry is a costly endeavour. Teaching undergraduate and postgraduate students how to perform experiments is one thing. However, teaching those students how to operate expensive equipment in low-resource environments has proven to present a significant financial challenge. As a result, a large amount of teaching on expensive equipment is relegated to the demonstration of the equipment by an experienced technician. However, this does not provide students with the hands-on training that is required to run the equipment and perform the experiments themselves.

Digital twin laboratories, accessible through low-cost, portable virtual reality headsets, have revolutionised chemical education and collaboration. These immersive environments replicate physical laboratories, offering unique platforms for experiments, laboratory tours, and training on specialist equipment, thereby offering novel platforms for hands-on training. An advantage of the approach of digital twins is the integration of conversational artificial intelligence avatars. These avatars, while using ChatGPT in the background, can be trained to prevent the "hallucination" of the large language models. Another advantage of using large language models

in digital twin laboratories is that they provide access to "non-English" avatars. While this has been shown in the past by using avatars speaking German or Spanish, we envisage that avatars speaking various South African languages would increase our students' understanding through mother-tongue education.

In this contribution, we describe the state-of-the-art technology in digital twin laboratories for education. We propose our road map to develop these digital twin laboratories for education and collaboration in low-resource environments. In conclusion, we describe how these digital twin laboratories can be used for collaboration and remote education of potential users. By combining digital twin laboratories with digitally manufactured hardware, initial training can be provided in virtual reality, before the student engages with the actual hardware. This approach results in increased user familiarity which minimises potential damage.

**Keywords:** Digital chemistry; Digital twin laboratory; Mother-tongue education; Virtual reality

## 1. Introduction

While the concept of virtual reality (VR) has existed since the 1960s, its early iterations suffered from poor graphics and were dismissed as a passing trend. However, over the past few years, accelerated by the coronavirus disease 2019 (COVID-19) pandemic, researchers explored the potential uses and benefits of incorporating extended reality in their work. It is well known that hands-on laboratory experience is a fundamental training component that enables students to develop practical skills. Hands-on training prepares students for their future careers and remains an indispensable part of science education. However, scientific laboratory equipment is often limited because of financial constraints, safety concerns, or availability. This limits educators in delivering a comprehensive laboratory education, particularly in fields such as chemistry, where the cost of equipment is prohibitive for many African institutions. Thus, educational training barriers for certain students would limit their potential in the post-education job market.

The importance of seeking alternative approaches to in-person instruction has been well-documented since 2020. Multiple methods were developed within the Science, Technology, Engineering and Mathematics (STEM) subjects, including using augmented reality and simulations, to deliver experimental training during the COVID-19 pandemic (Dukes, 2020; Tran *et al.,* 2020; Petillion & McNeil, 2021). However, while two-dimensional (2D) information, short videos, and online instruction present some substitution of in-person instruction, it does not provide the rich learning experience of a real laboratory. Enabling technologies like VR could augment the training by providing a rich, three-dimensional (3D) environment. The simple, low-cost addition of a VR headset of approximately R15,000 could prepare students for laboratory training by interacting with a virtual twin of the laboratory. As a result, students could gain important experience in setting up dangerous experiments or preparing expensive equipment without any safety concerns.

The COVID-19 pandemic spurred research into how well VR applications may bridge the gap between remote learning and hands-on laboratory experience. Chan *et al.,* (2021) demonstrated that VR experiences provide a more immersive experience, especially when students are expected to later actively complete a practical task. VR experiences were comparable to in-person training in a laboratory environment (Chan *et al.,* 2021). Virtual reality for Chemical Sciences (broadly speaking Chemistry, Biochemistry, and Chemical Engineering) is well documented. VR provides a powerful visualisation tool for atomic orbitals, stereochemistry, and molecular modelling (Dai *et al.,* 2020; Maksimenko *et al.,* 2021; Seritan *et al.,* 2021; Fombona-Pascual *et al.,* 2022; Zhao *et al.,* 2022). In addition, it can be used to effectively train students in experimental techniques when the actual chemicals are either too dangerous or expensive (Dunnagan *et al.,* 2020; Cañ o De Las Heras *et al.,* 2021; Qin *et al.,* 2021; Gallardo-Williams & Dunnagan, 2022; Wang *et al.,* 2022; Stella *et al.,* 2023). Furthermore, VR provides a useful educational tool for laboratory safety training (Kong *et al.,* 2022). These examples show that access to VR training provides a safe, immersive experience that comes close to actual in-person training. Digital twin environments would offer students a realistic environment

and provide opportunities to engage with and manipulate realistic representations of laboratory equipment and procedures. Therefore, creating immersive learning environments will prove crucial in the future of education for experimental sciences.

## 2. Building a Virtual Twin Environment

Digital twins can be defined as a precise virtual representation of a physical object, laboratory, or building. To make this digital reflection of a laboratory as accurate as possible, telemetry is used for up-to-date information exchanges between the virtual and real worlds. The concept gained significance in the context of the Fourth Industrial Revolution and its technological advancement, including the Internet of Things (IoT) and low-cost VR headsets. This enables the creation of precise digital twin environments for students, which are exact virtual replicas of laboratories, and control real-time scientific data. To build a realistic digital twin, it is recommended that the actual laboratory floor plan be measured. Detailed items, such as equipment, can be constructed in computer-aided design (CAD) software. As an introduction to CAD software, the author prefers that new students start with TinkerCad. TinkerCad contains an electronics module, making the teaching of Electronics and Arduino easier, thus providing a pathway towards Robotics as well. While TinkerCad is not an advanced CAD solution, it is freely available and has numerous tutorials to get started. TinkerCad is compatible with Fusion 360 (now called Fusion), and this advanced CAD software from the same company can be easily learned once the basics have been learned in TinkerCad. Of course, any CAD software can be used to design the various elements of the laboratory environment, although the files might not be compatible with CAD solutions.

To enable retention of information, it is beneficial to provide an exact replica of the teaching laboratory, with details such as equipment location and laboratory glassware (Figure 8.1) being identical (Gungor *et al.,* 2022). This enables the student to practice using the equipment and laboratory inventory without the associated risks caused by inexperience. Once the various pieces of equipment and laboratory inventory are produced in the CAD software of choice, they can be imported into a real-time

3D creation tool for the development of video games (Figure 8.2) (Taylor *et al.*, 2024). The best-known game engines are Unity and Unreal Engine. These game engines allow the user to build expansive and immersive environments which can be packaged for either desktop use or use with a VR headset.



**Figure 8.1:** (a) Laboratory glassware on shelves; and (b) a reaction setup in a fume hood (Gungor *et al.*, 2022).

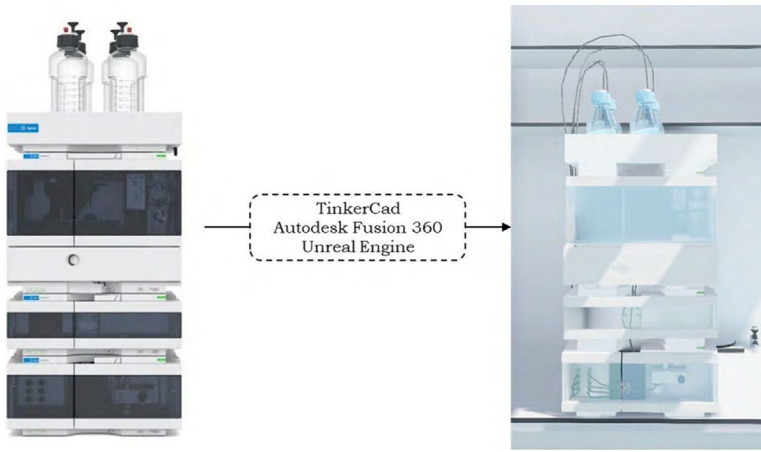



**Figure 8.2:** An high performance liquid chromatograph (HPLC) which was modelled using TinkerCad and Fusion 360. The model was then imported into Unreal Engine (Taylor *et al.*, 2024).

The VR software can be designed in both a single-user and a multi-user mode so that students can repeat the session if desired. For instructional purposes, it is desirable to be able to have multiple users logging in at the same time. Thus, students and multiple instructors could be present in VR. Having multiple students and instructors accessing a shared session allows better communication and allows the instructors to guide the students through the VR world.

Conversational AI avatars are available from companies like ConvAI (www.convai.com). ConvAI avatars are primarily created for the online gaming industry but have potential for scientific education as well. ConvAI allows designers to integrate conversational avatars into their existing software (Figure 8.3) (Taylor *et al.*, 2025), without the need to program the generative large language model. These avatars can be trained using knowledge banks of information that were input by the designer in the form of plain text files. Using this knowledge, the underlying large language models are prevented from generating inaccurate or inconsistent responses. The so-called character biography modifies the "personality" of the avatar and the responses provided. ConvAI avatars can speak and understand up to four languages per avatar. An impressive range of languages is available at the time of writing, but unfortunately, no South African languages (SeSotho, isiZulu, isiXhosa, etc.) are currently available.




**Figure 8.3:** ConvAI avatars allow the designer to customise features such as appearance, personality, language, training information, and the avatar's backstory (Taylor *et al.*, 2025).

## 3. Use of VR in Training

As mentioned earlier, VR environments were used to educate students in a range of subjects within the broader field of Chemical Sciences. Here we will not focus on educational solutions for understanding standard high school concepts such as the structure of an atom, or 3D molecular structures. The sole purpose of this overview is the training of students for experiments, in other words, the use of digital twins for training. Earlier, we stated that students can be trained to perform experiments in VR before they move to perform these experiments in the laboratory (Figure 8.4) (Gungor *et al.,* 2022). In a paper by Gungor *et al.*, (2022), it was noted that training the students in VR first reduced the level of anxiety, and improved the interest, and conceptualisation of the experiments. These findings address the potential value of the use of VR applications in higher education, especially in cases where the laboratory is not equipped to perform the experiments.

The Hilton research group (Taylor *et al.*, 2024, 2025) has recently pioneered the use of VR training, and they train a large number of students using VR. Some of the initial training was linked to a 3D-printed flow chemistry set-up. Because they had the CAD models on hand, it made sense to train students in VR. They expanded this concept by using a full digital twin of their laboratory environment, which can now be accessed by a large number of people.




**Figure 8.4:** Students train on continuous flow equipment in real life (left) *versus* digital world collaboration *via* multiuser capability (right) (Taylor *et al.*, 2025).

After the initial success of building a digital twin of their laboratory and importing the CAD drawings of their 3D-printed flow set-ups, the Hilton group moved on and started using VR to teach the use of expensive equipment. They used high-performance liquid chromatography (HPLC) for training in VR.7. A course was built in VR centred around four rooms (Figure 8.5). The first room introduced the session and taught students the use of the controls. In the second room, a video demonstration of the use and theory of HPLC was viewed. In room three, the students could interact with the HPLC instruments and had to perform activities such as connecting columns, connecting solvent bottles, and placing samples in the sample changer. In the final room, a discussion about HPLC traces took place and the session was wrapped up. If students became nauseous, they could take their VR headsets off for the sessions in Room 2 and Room 4 and view the video on a normal screen (see Figure 8.5). It was noted that a large number of students could be trained using this VR environment in a single day – significantly more than a normal laboratory session could train.

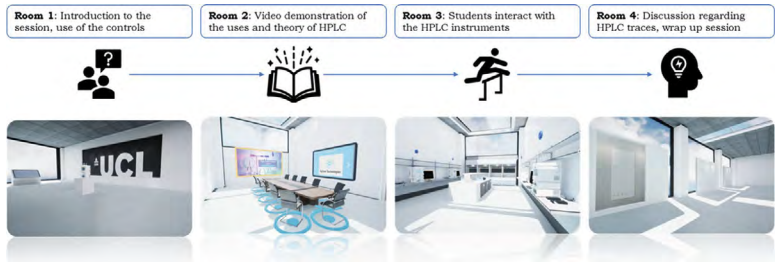



**Figure 8.5:** Software design of multiple rooms designed to optimise the VR experience (Taylor *et al.*, 2024).

The students were asked to complete a short questionnaire with questions on a scale of one to five, with one being dissatisfied and five very satisfied with the VR laboratory experience. The overall feedback was very positive, with students responding that the practical was enjoyable. The students also reported that the experience improved their understanding of chromatography in general and HPLC specifically. See Figure 8.6 for the feedback from the students.

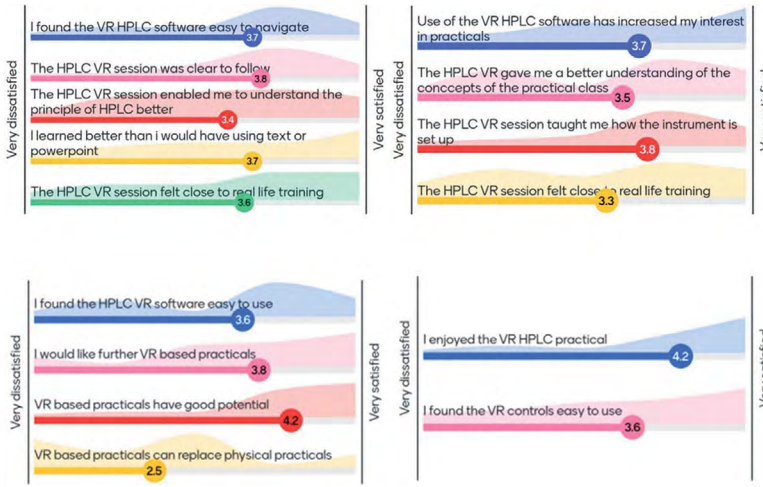



**Figure 8.6:** Feedback on the VR HPLC training workshops (Taylor *et al.*, 2024).

The next step in the VR training is the inclusion of conversational AI avatars (Taylor *et al.*, 2025). As mentioned earlier, these conversational AI avatars are driven by generative large language models (LLMs). However, the conversational AI avatars can also be trained by including a so-called knowledge bank of information. This knowledge bank will increase the accuracy of the conversational AI avatar and reduce the so-called "hallucination" of LLMs. It was reported by Taylor *et al.*, (2025) that the accuracy of the conversational AI avatars was impressively accurate. Three conversational AI avatars were trained. The first conversational AI avatar was given a knowledge bank containing the location, sub-location, CAS (chemical abstracts service), and stock code for all 1,026 chemicals within the laboratory. A second conversational AI avatar was given a knowledge bank with the complete inventory of consumables, with a list of locations in the laboratory. The third conversational AI was provided with a knowledge bank containing risk assessments and safety rules. It was found that the three conversational AI avatars were exceptionally accurate in their feedback to various questions.

To broaden the scope of education, these conversational AI avatars can converse in a range of languages. Conversational AI

avatars can "speak" up to four languages. The previously described platforms, based on a digital twin platform, were initially equipped with trained conversational AI avatars. Subsequently, additional multilingual avatars were included to democratise access to expensive, sophisticated, or dangerous equipment. Thus, the training on HPLC evolved from in-person training, via VR training, to training in VR with conversational AI avatars who speak several languages (Figure 8.7) (Al-Dargazelli *et al.*, 2024). These multilingual AI avatars make training on dangerous reactions, or sensitive or expensive equipment to a large range of the population (Figure 8.8). While multiple languages are natively available for ConvAI avatars, unfortunately, there are currently no South African languages available. However, the author hopes that these languages will become available in the near future.




**Figure 8.7:** The evolution of HPLC training: from in-person, via VR training to training with conversational AI avatars (Al-Dargazelli *et al.*, 2024).




**Figure 8.8:** (a) an example conversation about HPLC in English; (b) example conversations in German and Spanish (Al-Dargazelli *et al.*, 2024).

## 4. Conclusion

Virtual reality (VR) is significantly revolutionising the educational landscape. Through the use of VR, educators could teach students how to set up reactions and how to perform analyses using expensive equipment normally out of reach for undergraduate and postgraduate students. The technology is easily scalable, with adding more VR objects in a designed VR environment being a relatively easy task to perform in the software. VR offers a new approach to overcoming the prohibitive costs associated with training and acquiring cutting-edge equipment. Students have reported a greater sense of engagement by engaging in VR with equipment, compared to traditional text and PowerPoint presentations. The integration of VR into the education of the Chemical Sciences represents a transformative shift. Using VR, we can overcome the obstacles normally associated with scientific education, namely, a lower cost and a danger-free environment. Students are reporting an immersive experience that supports their problem-solving skills and ability to tackle real-world problems related to their studies. This immersive experience can be enhanced by integrating robotics into VR. Several researchers are currently developing the VR equivalent of their real-world robotic systems. By using telemetry, data from the real laboratory can be streamed to the VR laboratory, where researchers can engage with the data in real-time. While there are more examples in the literature of VR in Chemical Sciences education, the presented examples in this short chapter have specific relevance to the South African educational landscape. By using VR training on expensive equipment, students visiting another institution can be prepared before they operate the equipment. Safety training and other aspects of the training could, in the near future, be performed in the students' mother tongue by using ConvAI avatars. By combining training in VR with flow Chemistry and low-cost robotics, we can prepare our students for the world of tomorrow.

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# Chapter 9

# How Low Can We Go: Low-Cost Flow-Chemistry for Education

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## Abstract

The adoption of continuous flow synthesis in Chemistry, so-called flow chemistry, has increased significantly over the past several years. Continuous flow systems provide improved reaction safety and accelerated reaction kinetics and have synthesised several active pharmaceutical ingredients in automated reconfigurable systems. Although continuous-flow platforms are commercially available, these systems are currently prohibitively expensive and unnecessarily fragile, making them impractical for many applications. While continuous flow chemistry is steadily increasing its footprint in academic research and the manufacturing of pharmaceutical intermediates and fine chemicals, the attention to flow chemistry in educational programmes remains, on average, rather limited. The high costs of flow chemistry account for the limited use in educational programmes. We, and others, have described a "do-it-yourself" approach to flow chemistry to democratise this enabling technology. If we are to perform research using flow chemistry, then it only makes sense to introduce this technology as early as possible in the educational curriculum. Using this do-it-yourself approach brings the costs of flow chemistry set-ups down so much that it can be

potentially introduced into the undergraduate curriculum. These systems can also be used in outreach activities to other resource-constrained universities and high schools. In this contribution, we describe the state-of-the-art flow chemistry systems. Subsequently, we turn our attention to lower-cost DIY flow chemistry systems, including our work on 3D-printed flow chemistry systems. Finally, we discuss several reactions performed with these low-cost systems as potential reactions to be introduced into the undergraduate curriculum. We will demonstrate that by using digital manufacturing technologies like 3D printing, we can build low-cost but high-concept flow chemistry systems that can be mass-produced for large groups of undergraduate students.

**Keywords:** Digital manufacturing; enabling technologies, flow chemistry; maker skills

## 1. Introduction

The field of Chemistry, despite its long history and advancement in synthetic techniques, still relies heavily on manual techniques reminiscent of cooking. While synthetic methodologies have evolved over the years, the act of performing chemical reactions is similar to how it was performed two hundred years ago. The current chemistry research laboratory would be instantly recognisable to a chemist from two hundred years ago. The chemist still collects hardware such as round-bottom flasks and reflux condensers and puts them together to perform a reaction. These reactions, in practice, are still carried out by hand. Consequently, highly skilled chemists spend an inordinate amount of their valuable time on manual reactions.

The last hundred years have seen an astounding advancement in the understanding and synthesis of organic compounds. In contrast, laboratory technology has remained much the same; reactions are still labour-intensive and are performed in round-bottom flasks, housing stirrer bars and reflux condensers. Although this style of chemistry, termed batch chemistry, is often suitable for chemical transformations,

research has shown that continuous flow can provide a range of benefits. Thus, in traditional Chemistry, a reaction set-up is built, and one reaction is performed in that set-up. If the chemist wants to produce a larger amount of the chemical that they are synthesising, then the reaction needs to either be repeated or scaled up; in other words, performed in a larger flask. It is this scaling up that presents problems for the trained chemist. In scaling the reactions up, several effects that might lower the yield of the reaction, aspects such as mass transfer limitation, hot spots, and localised higher concentrations could result in less-than-desired yields.

At the end of the twentieth century, several researchers moved from batch-type reactions to flow reactions. These researchers would perform reactions in a tube, rather than in a flask, and under continuous flow. The advantage of this approach is that, once the reaction conditions are optimised, scaling up is rather trivial. When more product is required, you can either run the reaction for a longer time or simply scale out by using more reaction set-ups. Essentially, continuous flow chemistry is achieved by pumping solutions of reactants through reactors in a continuous manner. For lab-scale purposes, syringes, high-performance liquid chromatography (HPLC) systems, or peristaltic pumps drive fluid through reactor coils or microfluidic chips, with the residence time of the fluid dictated by the total flow rate and the reactor volume. Although single reactor coils are commonly used, advancements in in-line technology have provided opportunities to explore more complex, multistep transformations. In this context, "in-line" refers to a manipulation, or analysis, of the continuous flow stream without the solution exiting the continuous flow system.

Early flow chemistry research necessitated new equipment to perform the reactions. The building of this so-called flow chemistry equipment resulted in several spin-off companies. These companies are currently still in the market and sell their equipment at a relatively high price. For the South African market, this translates to approximately R500k for a set-up in 2025.



**Figure 9.1:** Commercially available flow chemistry set-ups: a) the Vapourtec E-series; and b) The Syrris Asia Starter Flow Chemistry system.

Basic flow chemistry set-ups generally rely on several essential components. There is typically a pumping solution, either peristaltic pumps, syringe pumps, or reciprocating syringe pumps. In Figure 9.1, we can see that the Vapourtec system comes with peristaltic pumps, and the Syrris Asia system uses reciprocating syringe pumps. After the pumping solution, there are typically coiled reactors, which are heated or cooled to the appropriate temperature, depending on the reaction performed. Alternatively, chip reactors can be used. Finally, a back-pressure regulator ensures that the reaction is run at a certain pressure. These back-pressure regulators are typically used when the reaction is performed at a temperature higher than the boiling point of the solvent used. More advanced set-ups require various parts that form the flow chemistry set-up. This can consist of biphasic separators, mixing columns, fixed bed reactors, stirred tank reactors, and so forth. Purchasing these parts from flow chemistry suppliers can be quite costly.

Commercially available set-ups have proven to be too expensive for educational purposes in a resource-constrained environment. With an average group of thirty to fifty students at a second-year BSc level, it becomes cost-prohibitive to teach flow chemistry. Recently, several authors have described lower-cost flow chemistry set-ups in the literature (Britton & Jamieson, 2027). In addition, with the advent of digital manufacturing technologies, such as three-dimensional (3D) printing,

laser-cutting, and Arduino electronics, becoming rather inexpensive, several authors released the designs of completely home-built flow set-ups at a low cost (these will be described later). We contend that by building open-source flow chemistry set-ups, we can bring flow chemistry to the undergraduate teaching laboratory.

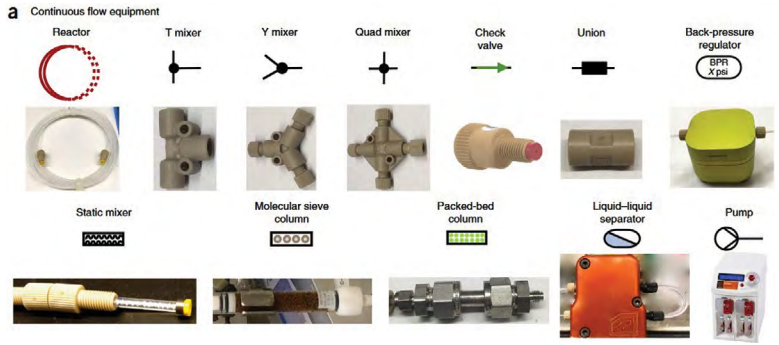



**Figure 9.2:** Typical pieces necessary to build a low-cost flow chemistry setup (Britton & Jamieson, 2027).

While building a flow chemistry set-up from standard laboratory pieces is more cost-effective than purchasing a commercial flow chemistry set-up, this is still too costly for the teaching laboratory. We will describe how to build these lower-cost systems, though, as this can link the teaching laboratory practice to the research laboratory, should one need to. In Figure 9.2, the typical lower-cost parts are presented, with their symbols depicted above them (Britton & Jamieson, 2027). We see a coiled reactor, which can be heated using a conventional stirrer hotplate, several mixers (T-, Y-, quad-mixers), a check-valve, a back-pressure regulator, a static mixer, some columns, a liquid-liquid separator, and a pumping solution. These components can be home-built, but the overall cost remains too high for the undergraduate teaching laboratory. The commercially available pumping solutions, such as syringe pumps and peristaltic pumps, are pricey, costing in the order of R35.000 each from Sigma-Aldrich (https://www.sigmaaldrich.com/ZA). Other high-cost parts of these set-ups are the prohibitively expensive back-pressure regulators (Zaiput ~R40.000 each) and

liquid-liquid separators (Zaiput ~R100.000 each). Finally, the mixers and connectors are all off-the-shelf polyetheretherketone (PEEK) fittings, which are relatively expensive. Currently, Upchurch PEEK fittings cost about R1,000 to R,1500 for ten, whereas unions (R1,000 for one), tees (R1,000 for one), and crosses (R1,100 for one) are more expensive at Sigma-Aldrich. While the costs of these PEEK fittings are within the budget of a research laboratory, they are still too steep to justify for use in the teaching environment.

For continuous flow chemistry to truly revolutionise research and education, the apparatus should be modular, so that it can be easily replaced to create a variety of systems. Envision a system that is quick to assemble from readily available and cost-effective parts, and easy to operate, allowing both new and experienced students to harness the benefits of continuous flow chemistry. For example, the synthesis of a published pharmaceutical compound requires multiple syringe pumps with syringes, reactor coils, a back-pressure regulator, and an in-line liquid-liquid separator. To then synthesise another pharmaceutical component, students need to re-arrange the syringe pumps, add a new reactor coil, and then exchange a static mixer for a back-pressure regulator. This process is fast and allows the synthesis of another pharmaceutical component. This is the key to accelerating discovery and making advanced chemistry techniques available to everyone.

Even the most basic, the low-cost approach, as advocated previously (see Figure 9.2) (Britton & Jamieson, 2017), remains financially out of reach for the standard teaching laboratory. Perhaps the simplest set-up for flow chemistry would consist of two syringe pumps, a PEEK Tee, a coil reactor, and a back-pressure regulator, assuming that all the other necessary parts (stirrer hotplates, oil baths, thermometers) are already present in the laboratory. The cost of these components would still be in the region of R110.000 based on the costs of the parts mentioned above. Adding more components, such as reactors, syringe pumps, and other equipment, would incur more costs, making even this simple set-up too expensive for the teaching laboratory. Ultimately, flow chemistry ends up perhaps being too expensive for research in resource-restricted environments.

## 2. Enabling Technologies

### 2.1. 3D printing and Arduino Electronics

Three-dimensional printing is an enabling technology for flow chemistry. There are various technologies described in the literature for 3D printing, but here we focus on fused filament printing and resin printing as technologies to rapidly build flow chemistry set-ups at low cost. Fused filament printing is the most popular and cheapest technology. It involves the melting and solidification of a thermoplastic filament. In a typical procedure, a fresh thermoplastic filament is continuously fed into a heated chamber in the 3D printer called the extruder. The molten polymer exits continuously in a threadlike manner through the nozzle. Then, the nozzle is lowered to a levelled surface known as the print bed. As the molten filament gradually exits the nozzle in a controlled manner, a layer-by-layer pattern is created on the print bed, depending on the speed and the computer-aided design (CAD) (Alimi & Meijboom, 2021).

The 3D printing process is divided into two major steps, namely CAD and printing. The initial step is to develop a CAD. You can create it using a 3D scanner, downloaded freely from open-source Web-based 3D printing communities (e.g., Thingiverse, www.thingiverse.com), or create your own in an appropriate 3D creation software (e.g., FreeCAD, Tinkercad, or Onshape). The model is usually exported as a stereolithographic file (STL), which is easily converted to a computer numeric control (G-code) programming language to initiate printer control and movement using so-called slicing software, for example, Slic3r (https://slic3r.org/). The G-code file is copied to the 3D printer. The 3D printer proceeds to fabricate the object directly using layer-by-layer deposition of the molten filament on the print bed (See Figure 9.3) (Alimi & Meijboom, 2021).

The flexibility of 3D printing technology allows the fabrication of different properties for chemistry and chemical applications. This is because of the availability of a range of commercially available thermoplastic filaments, such as polylactic acid (PLA) and acrylonitrile butadiene styrene (ABS). Moreover, with increasing awareness of 3D printing technologies, other varieties of thermoplastic materials with

suitable properties are becoming commercially available. This includes polypropylene (PP), PEEK, and nylon, amongst others. Other printable materials include ceramics, metals, and oxides of metals.

Another method of 3D printing is the so-called stereolithography (SLA) printing. SLA printing is an additive manufacturing process that uses a light source to cure liquid resin (typically acrylates) into hardened plastic, layer by layer, creating 3D objects. This technology typically uses a type of vat photopolymerisation, where liquid, photosensitive resin is poured into a vat. The light source, either a laser or a screen, selectively cures the resin, layer by layer, solidifying it into the desired shape. All initial steps, as described before for fused filament printing, are the same; the major difference between SLA and fused filament fabrication (FFF) printing is the materials and the resolution of the final print. SLA printing typically results in a higher resolution printed object, whereas FFF printing is used typically for larger objects, and the resolution is in the order of 0.1 mm (see Figure 9.3 for some 3D printer examples).

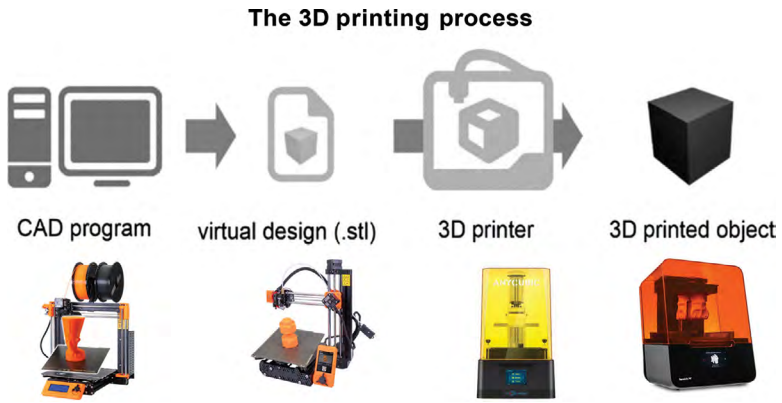



**Figure 9.3:** (Top) The 3D printing process: the first step is CAD. The CAD is saved as an STL file. After slicing, the G-code is exported to the 3D printer. The 3D printer prints the final object. (Bottom) We have several 3D printers in our laboratory at the University of Johannesburg: a Prusa MK3S, a Prusa Mini+ (Fused filament printers), as well as an Anycubic Photon, and a Formlab Form 3 (both SLA printers).

The revolution in open-source hardware, exemplified by Adrian Bowyer's RepRap project (https://reprapltd.com/), was fuelled by the Arduino microprocessor boards (https://www.arduino.cc/). Arduino, an Italian open-source company, project, and user community, designs and manufactures single-board microcontrollers and microcontroller kits for building digital devices. The hardware products are licensed such that the manufacture of Arduino boards and software distribution are allowed by anyone. Arduino boards are commercially available from several distributors, and there are numerous low-cost clones available. Arduino boards use a variety of microprocessors and controllers and were designed specifically for use by anyone. The Arduino project allows non-specialists to use microcontrollers and build electronic projects. The project began in 2005 as a tool for students at the Interaction Design Institute Ivrea in Italy. The project aims to provide a low-cost and easy way for novices and professionals to create devices that interact with their environment using sensors and actuators. Notably, the electronics that drive a plethora of commercial and open-source 3D printers are Arduino variants.

The technologies of CAD modelling, 3D printing, and the use of Arduino open-source hardware are easy to learn for anyone who is careful and precise enough. The author has given simple workshops to numerous students, teaching the fundamentals of CAD modelling, 3D printing, and Arduino electronics. Many students have already benefited from these workshops.

## 2.2. 3D Printed Equipment for Flow Chemistry

Three-dimensional printed flow chemistry equipment similar to the mentioned Vapourtec and Syrris equipment exists. This flow-chemistry set-up was mainly 3D-printed and fit around a commercial stirrer hotplate. A modular, air pressure-driven, flow chemistry set-up, designed by Stephen Hilton and his group, could be attached to existing (IKA) stirrer hotplates (Penny *et al.*, 2019). The design used PLA printed housing, with PP circular disk reactors (Figure 9.4). The system was driven by a pressurised gas cylinder, reducing the costs of pumping significantly, because most Chemistry laboratories have access to pressurised gases.

As the back-pressure regulator, a range of capillaries was used, resulting in a flexible system that could vary residence time in the reactors (Penny *et al.*, 2019).

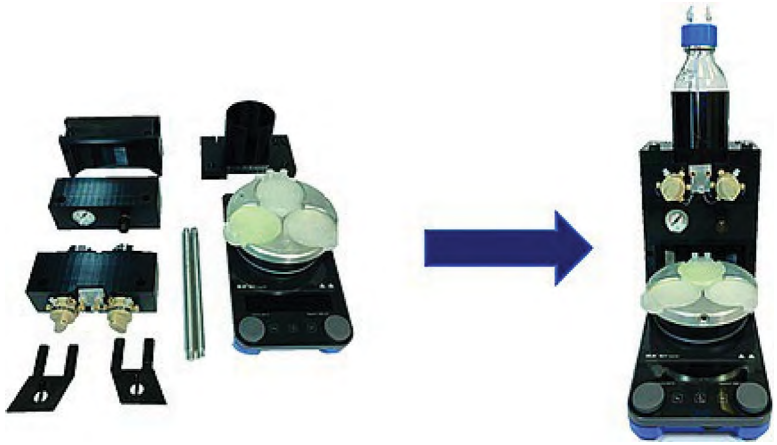


**Figure 9.4:** Hilton and co-workers designed a complete 3D printed flow chemistry solution with a PLA body (black) and PP circular disk reactors (Penny *et al.*, 2019).

The 3D-printed set-up appeared to work quite well, facilitating several successful reactions (Penny *et al.*, 2019). However, its subsequent commercialisation by IKA (https://www.ika.com) rendered the set-up prohibitively expensive for the teaching laboratory. One drawback of the 3D-printed flow chemistry set-up was that the design files were not released to the public. This meant that you either had to redesign the files, contact the authors, or wait for the release of the files.

The Hilton system was updated in 2023, with additional solvent modules, but also with several sensors (Figure 9.5) (Montaner *et al.*, 2023). The system integrates several in-line sensors. They developed a PC interface platform to automate its functional control, including the injection of solvents and the visualisation of sensor-reported data. The utility of the system was demonstrated by performing a series of reactions showcasing how critical the precise control of solvent flow rate and accurate reporting of reaction temperatures are for standardisation and reproducibility. Furthermore, the system can be easily modified to

allow for scale-up synthesis. Interestingly, the Hilton group uses virtual reality (VR) to train new students on the use of these flow chemistry setups. Thus, new users are initially provided with a VR headset and are taken into VR to set up a system. After an initial introduction to the system in VR, the students are then instructed on a real system. This reportedly reduced the number of errors made by students (S. Hilton, personal communication).

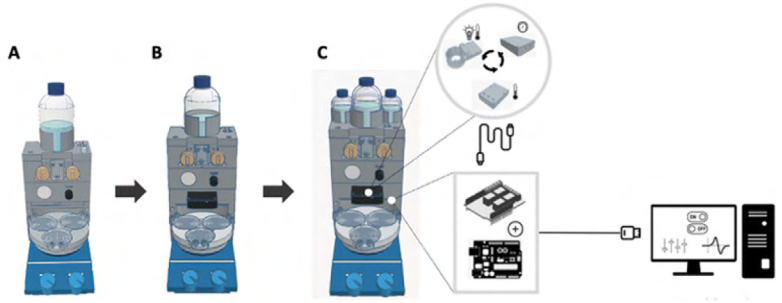



**Figure 9.5:** Tinkercad representative design of the proposed modular continuous flow chemistry system: (A) Analog system; (B) Digital system; and (C) Scale-up version of the digital system (Montaner *et al.*, 2023).

## 2.3. 3D-printed Syringe Pump Solutions

As discussed previously, some of the most expensive parts of do it yourself (DIY) flow chemistry set-ups are the pumping solutions. It is, therefore, not surprising that several 3D-printed syringe pumps have been released. The 3D-printed syringe pumps typically use a low-cost stepper motor and an Arduino microprocessor to drive the stepper motor. One excellent example of an open-source syringe pump solution is the Poseidon syringe pump (Figure 9.6), published by the Pachter group at Caltech (Booeshaghi *et al.*, 2019). This syringe pump is an evolution of one of the earliest open-source syringe pumps, published by the Pearce group at Michigan Technological University (Wijnen *et al.*, 2014). This syringe pump solution uses a Python script on a computer that is connected via a universal serial bus (USB) cable to the Arduino microcontroller. The Arduino microcontroller is fitted with a computer numerical control (CNC) shield containing stepper motor boards.

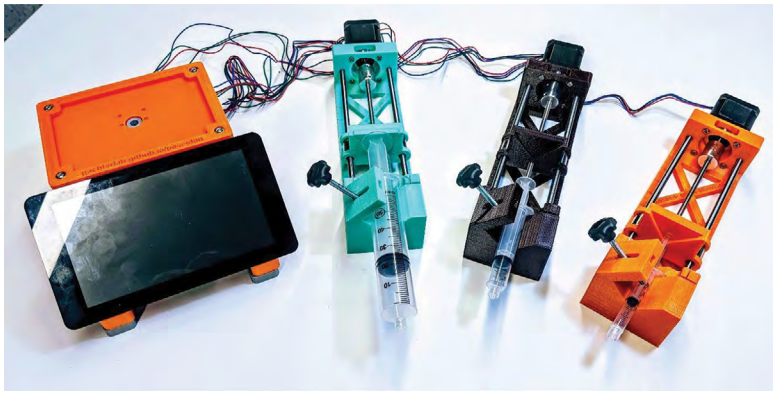


**Figure 9.6:** The Poseidon syringe pump rack with Raspberry Pi-driven microscope (Booeshaghi *et al.*, 2019).

The Poseidon syringe pump rack is an excellent solution for the introduction of flow chemistry. We have used this specific syringe pump rack extensively in our experiments at the University of Johannesburg. Another syringe pump rack that we used extensively was designed by Jochen Neumaier at the University of Tübingen in Germany (Neumaier *et al.*, 2019). Neumaier published a range of low-cost, modular, flow chemistry parts that are easily produced using simple 3D printers and Arduino boards. The initial pumping solution of Neumaier was a rather complex design (Figure 9.7). In our hands, the design was overly complex, and we rapidly moved from this design to the Poseidon syringe pumps. The advantage of the Neumaier design is that it comes with a separate controller box so that there is no need for a laptop to control the pumps (Neumaier *et al.*, 2019). This is obviously advantageous in a laboratory setting where chemicals can potentially be spilled on the laptop.

Neumaier followed his original design of syringe pumps with annual updates, first designing a 3D printed reciprocating syringe pump (Figure 9.7b), as part of a set-up with difficult-to-print PEEK reactors (Menzel *et al.*, 2020). This pumping solution allows continuous pumping of a solvent phase through the reactors. Finally, needing a syringe pump at higher pressure, Neumaier reported a high-pressure dual syringe pump with a geared stepper motor (Figure 9.7c) (Menzel *et al.*, 2023). These dual syringe pumps could pump liquids at higher pressures than the non-geared solutions reported earlier and allowed the use of back-pressure regulators.

It must be noted that a range of other syringe pumps and peristaltic pumps have appeared in the open-source hardware literature. I will not describe every solution for pumping solvents that appeared in the literature. However, I have provided some examples of 3D-printed pumps, which could lower the costs of flow chemistry and ensure the adoption of flow chemistry in the teaching laboratory.

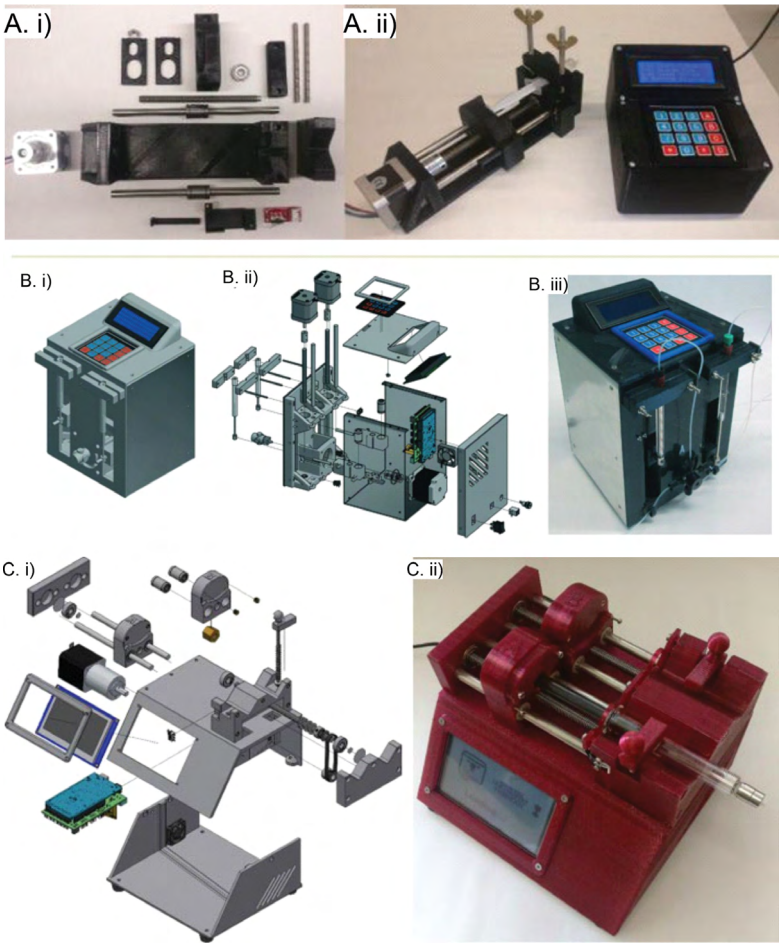



**Figure 9.7:** Neumaiers: a) 2019 syringe pump rack (Neumaier *et al.*, 2019); b) 2020 continuous syringe pump (Menzel *et al.*, 2020); and c) dual high-pressure syringe pump system (Menzel *et al.*, 2023).

## 2.4. 3D-Printed Reactors

We, and others, have 3D-printed a range of reactors, ranging from 3D-printed chip reactors printed from PP to stirred tank reactors and fixed bed reactors. Figure 9.8 shows several 3D-printed reactors used in our flow chemistry research (Alimi & Meijboom, 2021). The Neumaier group rapidly changed from printing PP reactors (Neumaier *et al.,* 2019) to using PEEK as a reactor material (Menzel *et al.,* 2020). 3D printing of PEEK, however, requires a rather expensive 3D printer, and thus, the PEEK printed reactors proved too expensive for educational purposes. In our hands, we could work well with the PP-printed reactors. Unfortunately, because of the low resolution of FFF printing, we encountered regular leakage on the connections. We then moved to resin printing for the chip reactors (Alimi *et al.,* 2025), using the higher resolution of resin printing and the almost inert nature of resin-printed objects. By using resin printing for chip reactors, we are also able to generate catalytically active chip reactors, enabling us to perform catalytic reactions without difficult separation of the catalyst after the reaction is completed.

A range of reactors was printed by us and others (Figure 9.8). So-called chip reactors are typically manufactured from glass and are rather expensive, with prices between R20k and R145k from Sigma-Aldrich. Neumaier and coworkers initially printed flow chips from PP (Neumaier *et al.,* 2019), and then moved to PEEK (Menzel *et al.,* 2020) as an inert material. We continued with the printing of our reactors in PP and developed a range of reactors: fixed-bed reactors (Onisuru *et al.,* 2021), stirred tank reactors, as well as biphasic separators (Alimi *et al.,* 2022). These 3D-printed reactors could replace the coil reactor, fixed- or packed-bed reactor, and biphasic separator, as depicted in Figure 9.8.

Recently, we started to redesign these reactors to be fully printed from acrylate resin using SLA printers. The advantage of using SLA printing is that the reactors are now completely clear, and the reaction is easy to observe. Another big advantage is that the SLA-printed parts have a significantly higher resolution, and

this ensures that the parts are leak-proof. With FFF printing, the resolution of the final part is not compact or uniform enough, leading to frequent connection leaks.

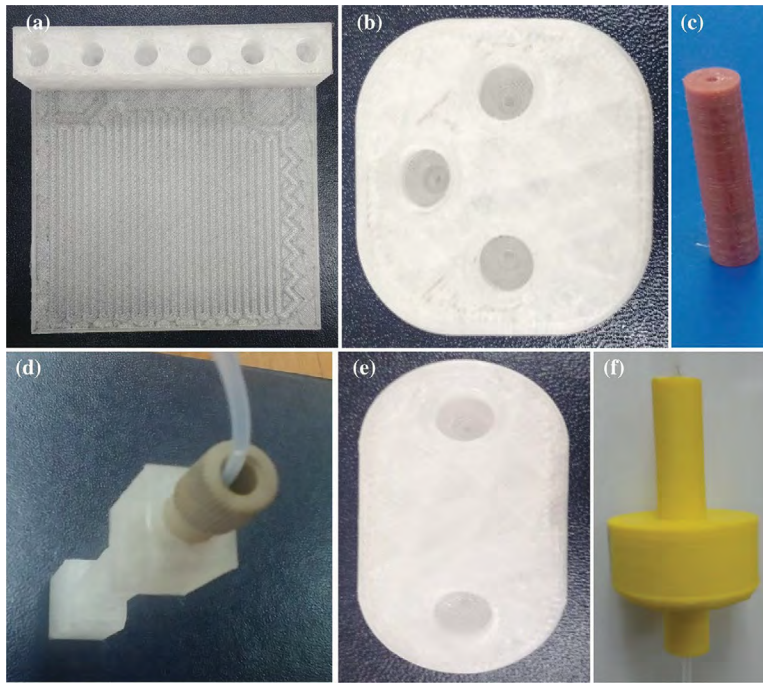



**Figure 9.8:** 3D printed reactors for flow chemistry: a) chip reactor; b) biphasic separator, c) fixed-bed reactor printed from PLA; d) fixed-bed reactor printed from PP; e) continuous stirred tank reactor; and f) fixed-bed reactor containing a monolith (Alimi & Meijboom, 2021).

## 2.5. 3D-Printed Fluidic Connectors

In 2021, Price *et al.*, reported on an open-source toolkit for teaching flow chemistry in undergraduate teaching (Price *et al.*, 2021). This toolkit used a rather difficult approach to printing fluidic connectors. The connectors were printed on a multi-material printer with the wetted parts being printed in PP, while the non-wetted parts were printed from PLA. We found

this approach overly cumbersome and redeveloped the toolkit for SLA printing. During our experiments, we found that the acrylate resins used in SLA printing were resistant to most solvents used in experimental chemistry. While the fluidic connectors are not the most expensive parts of flow chemistry, they are still overly expensive if we would like to teach flow chemistry in resource-restricted environments. Our 3D-printed fluidic connectors are depicted in Figure 9.9 (Alimi *et al.,* 2022).

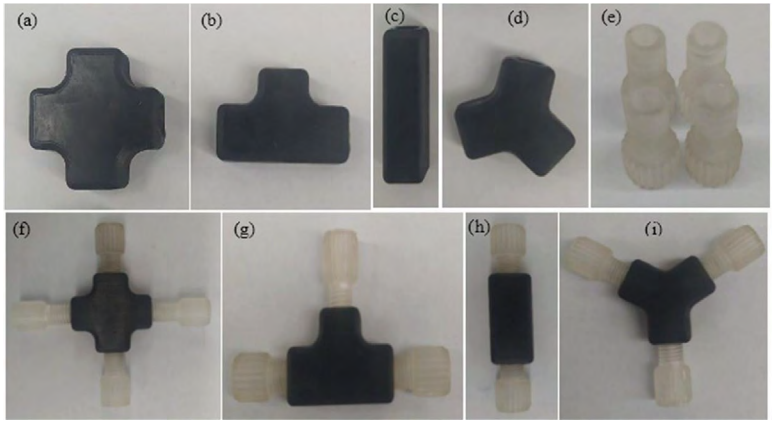



**Figure 9.9:** 3D printed fluidic devices: a) cross-connector; b) T-connector; c) straight union connector; d) Y-mixer; e) flangeless nuts; f) cross-connector assembly; g) T-connector assembly; h) straight union connector assembly; and i) Y-mixer assembly. All devices were printed on an Anycubic Photon Mono SLA 3D printer (Alimi *et al.,* 2022).

## 2.6. Back-pressure Regulators and Biphasic Separators

Commercially available back-pressure regulators either consist of spring-driven pressure regulators or consist of a flexible membrane where one chamber is pressurised with gases. The back-pressure regulator in Figure 9.10 is of the latter type, and is rather expensive. Back pressure regulators allow the reaction to take place at a higher pressure than atmospheric pressure, and this is beneficial if the reaction has to take place above the boiling point of the solvent. The higher temperature ensures faster

kinetics of the reaction. In addition, if a gas is formed during the reaction, the back-pressure regulator ensures that the gas remains in solution, and no gas bubbles are formed.

Neumaier reported a low-cost, spring-loaded, back-pressure regulator (Figure 9.10) (Menzel *et al.*, 2020). This back-pressure regulator consists of a silicone sheet and Teflon (PTFE) foil. The silicone sheet can be pressurised with a spring-loaded bolt. They reported that various springs could result in different pressure ranges up to 20 bar. The top parts, not in contact with the chemicals, were printed from conventional PLA. The parts in contact with the chemicals were printed from PEEK.

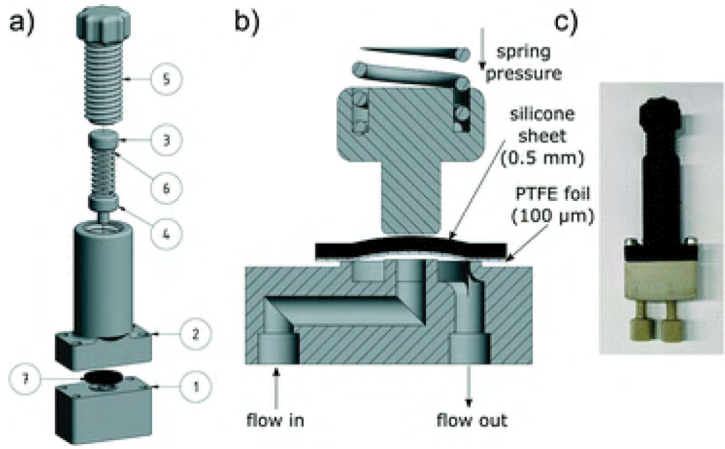



**Figure 9.10:** a) CAD of the initial back-pressure regulator; b) working principle; and c) printed device (Menzel *et al.*, 2020).

Subsequently, a motorised back-pressure regulator was reported by Neumaier and coworkers (Figure 9.11) (Menzel *et al.*, 2023). This motorised back-pressure regulator can be used to synthesise [$^{18}$F]2-fluoro-2-desoxy-d-glucose ([$^{18}$F]FDG), the most commonly used PET-tracer. These radiotracer compounds are best synthesised remotely, and, therefore, the group developed this motorised back-pressure regulator. While other back-pressure regulators have been reported on, we will not discuss these as the examples provided here are advanced

enough for the research laboratory, yet not too expensive to prevent adoption in the teaching laboratory.

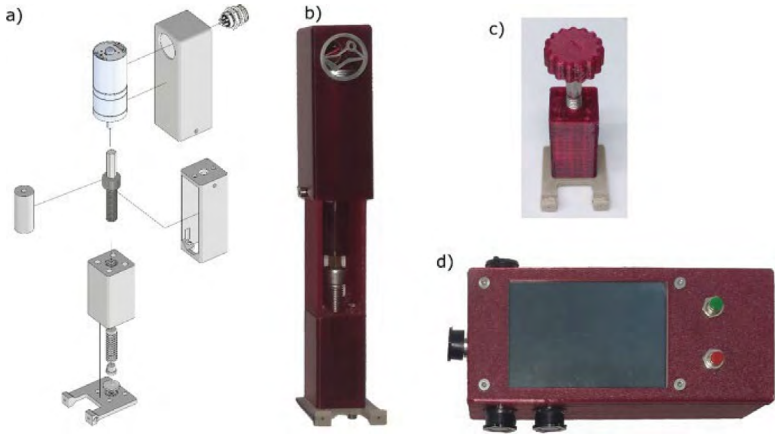



**Figure 9.11:** Exploded view CAD drawings and photographs of the motorised BPR (a, b); the manual BPR (c); and the control unit (d).

Biphasic separations are normally performed on a batch scale in the laboratory. The student or researcher uses a so-called separating funnel in which aqueous and organic layers are shaken to increase the interfacial surface area. Water-soluble impurities, typically salts, will be removed from the organic layer. After shaking the separating funnel, the two layers are allowed to separate, and a stopcock at the bottom is opened to separate the two layers into separate flasks for further work-up. For reactions in flow, we have already demonstrated that stirred tank reactors can be interfaced to increase the interfacial surface area. Separation of the two phases can then take place in reactors with an inlet in the middle and outlets at the top and bottom. One example of a PP printed phase separator is provided in Figure 9.8b.

Another approach to separate biphasic systems is to use an in-line separator. Neumaier and coworkers designed a simple membrane separator for biphasic separation (Figure 9.12) (Menzel *et al.*, 2020). This used a hydrophobic Teflon (PTFE) membrane clamped between two channels. The PTFE membrane had a pore size of 1 µm and a thickness of 100 µm and is commercially

available. For an effective separation of the two phases, a slightly higher pressure in the aqueous phase is needed. This pressure was achieved by placing the aqueous outlet tube 40 cm higher than the organic outlet tube. Again, the wetted parts were printed from PEEK in this example.

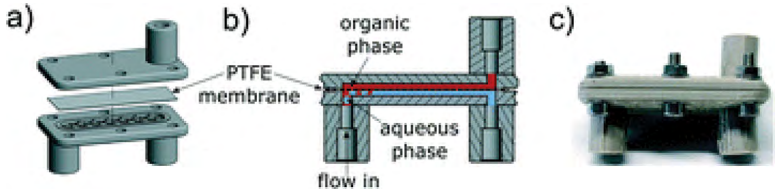



**Figure 9.12:** Biphasic membrane separator: a) CAD; b) principle; and c) printed device.

In this section of the chapter, I describe several parts of a flow-chemistry set-up. The parts can all be produced using simple, low-cost 3D printing. Most parts were developed initially using PP printing. The Neumaier group then went in the direction of PEEK printing for the wetted parts. At the University of Johannesburg, we are currently (2025) re-designing all wetted parts for resin printing. In our experience, resin-printed objects are suitable for conventional flow chemistry, and we have the freedom to formulate our own resins. The various parts necessary to teach flow chemistry in the undergraduate teaching laboratory are now available through 3D printing.

## 3. Costs of DIY Flow Chemistry Set-ups

The costs of building these flow chemistry set-ups are rather low. The majority of the above-mentioned parts of DIY flow chemistry are fabricated using either FFF 3D printing or SLA resin printing. Of course, an infrastructure will have to be built first to allow the printing of the various parts. I will provide a cost breakdown of the infrastructure necessary to print the flow chemistry set-ups, as mentioned in this chapter. As of 2025, the estimated costs are provided in Table 9.1. If we assume that linear bearings, smooth rods, threaded rods, and so forth will cost approximately R100 each, then we can calculate the approximate costs per flow chemistry item (Table 9.2).

**Table 9.1:** Approximate costs of infrastructure (3D printers) and parts necessary to build a low-cost flow chemistry infrastructure.

| Item | Approximate costs in rand |
|---|---|
| Prusa Mini+ 3D printer | R8,000 |
| Anycubic Photon Mono 4 resin printer | R4,000 |
| Anycubic wash and cure 2 | R1,800 |
| Polylactic acid 1 kg spindle | R300 |
| Polypropylene 1 kg spindle | R1,079 |
| High-temperature resin, 1 L | R755 |
| Arduino Mega 2560 | R400 |
| RAMPS1.4 | R180 |
| Stepper motor driver board a4988 | R30 |
| Arduino Uno | R158 |
| CNC shield | R40 |
| NEMA 17 stepper motor | R250 |
| Power supply 12 V | R600 |

**Table 9.2:** Approximate costs to fabricate the items mentioned in this chapter.

| Item | parts | Approximate costs |
|---|---|---|
| Infrastructure | Prusa Mini + 3D printer Anycubic Photon Mono 4 Anycubic wash and cure 3 | R8,000<br>R4,000<br>R1,800<br>**Total: R13,800** |

| Item | parts | Approximate costs |
|---|---|---|
| Poseidon syringe pump rack (3 pumps) | Arduino Uno<br>CNC shield + driver boards Stepper motors (3)<br>Power supply<br>Linear bearings, screws, smooth rod, and threaded rod | R158<br>R130<br>R750<br>R600<br>R1,000<br>**Total: R2,638** |

## 4. Typical Reactions for Educational Purposes

This section discusses some typical reactions for educational purposes using low-cost flow chemistry set-ups. The discussed reactions have all been utilised in an undergraduate educational setting. We focus on describing reactions that teach more than "just" flow chemistry. For instance, the first example focuses on teaching 3D printing and flow chemistry. The second example teaches the use of Statistical Design of Experiments in flow chemistry.

As research laboratories are diversifying their equipment by incorporating flow and automation technologies, it is also necessary for chemists to evolve at the same pace by diversifying their skill sets to fully harness the capabilities and ways of working enabled by this new equipment. Synthetic chemists are embracing facets of Process Chemistry, Chemical Engineering, Analytical Chemistry, and Programming, to name a few. Currently, there is an enormous drive towards so-called digital chemistry. Digital chemistry is the coming together of automation, maker skills ("hacking"), self-optimising reactors, data science, Statistical Design of Experiments, AI, and digital manufacturing. Flow chemistry is an ideal starting point for a number of these subjects.

### 4.1. The Synthesis of Aspirin and Acetobromo-α-D-glucose

First, we published the synthesis of aspirin, inspired by the batch reaction used in our undergraduate curriculum, using a 3D-printed flow chemistry set-up (Alimi *et al.*, 2022). The primary

pedagogical goal of this educational report is not only to empower the students with 3D printing skills but to expose them to the theoretical and practical fundamentals of flow chemistry. The aim was for students to simultaneously learn the basic concepts of experimental design, including synthesis, purification, relevant separation techniques, waste disposal methods, biphasic separation techniques, identification of organic molecules, and the use of digital manufacturing tools such as 3D printing and flow chemistry.

The set-up consisted of the afore-mentioned Poseidon syringe pump rack and a 3D-printed polypropylene chip reactor. The chip reactor was placed in a water bath and heated to 70°C. The reaction was quenched with water, and the mixture was pumped into an Erlenmeyer flask cooled with an ice bath. The synthesised aspirin crystallised in the Erlenmeyer flask at 0°C. The reaction in flow was compared to the manual reaction as performed normally in our undergraduate practical sessions. Figure 9.13 depicts the Poseidon syringe pump rack, the chip reactor in a 70°C water bath, and the start of the manual reaction (Alimi *et al.*, 2022).

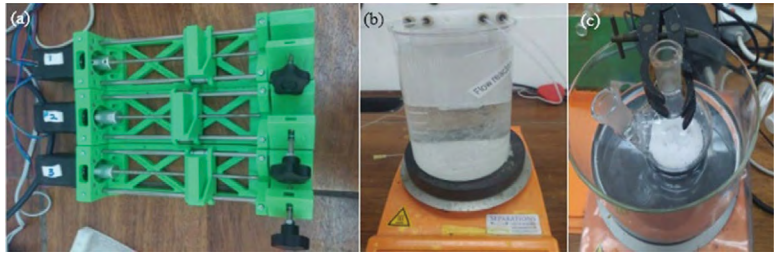



**Figure 9.13:** a) The Poseidon syringe pump rack used for the synthesis of aspirin in flow; b) the chip reactor in a water bath at 70°C; and c) the manual synthesis of aspirin (Alimi *et al.*, 2022).

The same study reported the manual and flow synthesis of acetobromo-α-D-glucose. This reaction is built upon the synthesis of aspirin by including biphasic separation in flow. This set-up, therefore, included stirred tank reactors and biphasic separators to initially increase the interphase of the water-organic

solvent, followed by a simple biphasic separation. The increased difficulty of the reaction taught the students additional skills for 3D printing and flow chemistry (Alimi *et al.*, 2022).

The study was performed using several third-year undergraduate students from the University of Johannesburg. The students 3D-printed the complete set-up using PLA-printing of the syringe pumps, PP-printing of the reactors, and finally, resin-printing of the fluidic connectors. Subsequently, the students performed the reactions in flow and batch, indicating that flow chemistry has a huge potential for teaching in the low-resourced undergraduate laboratory. It was reported that the students found the learning experience a positive one (Alimi *et al.*, 2022).

## 4.2. Statistical Design of Experiments in Low-Cost Educational Flow Chemistry

Implementing statistical training into undergraduate or postgraduate Chemistry courses can provide high-impact learning experiences for students. However, the opportunity to reinforce this training with a combined laboratory practical can significantly enhance learning outcomes by providing a practical bolstering of the concepts. Therefore, Bourne and coworkers (Taylor *et al.*, 2021) designed a simple, low-cost flow chemistry experiment for teaching in the undergraduate curriculum at the University of Leeds. The report includes a simple description of the Statistical Design of Experiments for undergraduate teaching.

In their paper, Bourne and coworkers (Taylor *et al.*, 2021) used a structured experimental design integrated with a flow chemistry platform. It was shown how this could be used as a teaching resource to introduce students to performing flow chemistry experiments and to better understand the type of data required for the optimisation of chemical processes. They reported a demonstration of the Statistical Design of Experiments for teaching the next generation of Chemistry in a practical lab setting, whereby a chemical process with several possible products is optimised for the highest yield of a particular product (Figure 9.14).

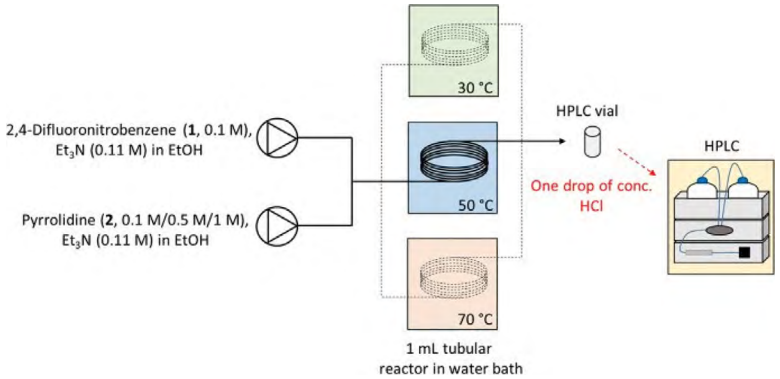



**Figure 9.14:** A schematic of the experimental flow set-up used for the $S_NAr$ reaction. The pyrrolidine concentration is changed for varying equivalent experiments, and the reactor is moved by hand into different water baths corresponding to the temperature that the experiment requires (Taylor *et al.,* 2021).

## 5. Conclusion and Call-to-Arms

The chemical educational landscape has significantly changed during this century. The era of traditional Chemistry, where chemicals are mixed by hand and then heated for a certain period, followed by manual purification, is coming to an end. Instead, Chemistry is increasingly using automation and robotics. Several new technologies are currently being developed, with flow chemistry being just one example. For us in sub-Saharan Africa, in resource-limited environments, we need to keep up with the worldwide changing technologies. But, how do we keep up with the ever-changing landscape of technologies and methodologies, and how do we teach the next generation of chemists? In the author's opinion, we need to engineer low-cost equivalents of the expensive teaching apparatus by making use of digital and distributed production methods.

Flow chemistry has been changing the approach to chemical synthesis and research in the last two decades. Initially, this was an expensive endeavour, and students were not taught flow chemistry worldwide. Slowly, flow chemistry was integrated into the curricula at resource-rich institutions. It is now clear that flow chemistry is here to stay, and we must adapt to this reality.

By using various digital production methods, such as 3D printing and laser cutting, combined with open-source hardware such as the Arduino ecosystem, we can bring flow chemistry to the undergraduate curriculum in Africa. However, this needs a systematic approach by several educators. The author has provided several examples of low-cost flow chemistry developed through 3D printing in this chapter. The examples, nonetheless, are rather heterogeneous, and most examples are disconnected from each other.

A systematic, low-cost approach to flow chemistry can only be achieved by re-educating our educators to utilise digital manufacturing tools and open-source hardware and electronics. Frustratingly, this is not as easy as it sounds! We will need to take the mentioned examples in this chapter and re-engineer them into one systematic approach to flow chemistry. The various "units" mentioned should be of the same standard, perhaps with a unified, underlying computer code to implement this in our undergraduate curriculum. By using home-built, research-grade equipment, we can prepare our undergraduates for the future. In this way, we can pre-build the various parts of flow chemistry and use them as "LEGO® pieces" to build full set-ups for the undergraduate curriculum, as well as research.

Flow chemistry as presented in this chapter is only the first step. The various pumping solutions presented here can be reconfigured to start robotic chemistry set-ups. Low-cost robotic chemistry set-ups, however, are the subject of another chapter. Another approach to teaching flow chemistry is currently being taken by the Hilton group. These researchers initially teach the use of their flow chemistry set-up in virtual reality (VR), before students start working with the actual hardware. Thus, we can develop an integrated approach to flow chemistry, from initial design, to DIY the various parts, to teaching in VR.

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# Chapter 10

# Chemical Cobots: Rise of the Frugal Educational Twin

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## Abstract

The field of Chemistry has witnessed a recent revolution in automation and robotics. However, most reported systems in the literature, from automated synthesis machines to robotic systems to self-driving laboratories, are simply too costly for widespread adoption. While some systems, such as automated chemical synthesis systems, are home-built, others use off-the-shelf robotic systems. Most of these robotic systems work collaboratively: so-called "cobots". Despite these systems being prohibitively expensive, we still need to prepare our students, at both undergraduate and postgraduate levels, for the world of tomorrow. This includes familiarising them with automated and robotic systems in Chemistry. In 2024, the concept of a "frugal twin" emerged in the chemical literature. A frugal twin is a low-cost demonstration system performing the same, or similar to, a high-cost top-research system. Frugal educational twins provide hands-on experience in robotics and automation for Chemistry students without the high costs and risks typically associated with such equipment. They can also function as test beds for prototyping, and as a low barrier to entry for democratising robotics and automation. In this contribution, we describe our approach to frugal twins to introduce automation and robotics to our undergraduate and postgraduate curriculum in Chemistry. We introduce

the concept of a "frugal educational twin" where we embed an educational angle to the development of low-cost, high-concept DIY robotics in Chemistry. This approach develops the research and educational aspects of this new branch of Chemistry. By embedding robotics and automation, through frugal educational twins, in our undergraduate and postgraduate curriculum, we can teach the concepts of these systems, thus, equipping the next generation of chemists to work with expensive systems.

**Keywords:** Automated chemical synthesis; Chemical cobots; Frugal twins; Maker skills

## 1. Introduction

Since Wilhelm Schlenk pioneered inert chemistry techniques and discovered the alkyl lithium reagents around 1917, synthetic chemistry has progressed to an incredibly subtle art. Over the last hundred years, synthetic pathways and new reactions have been discovered, and are still being discovered. However, while synthetic pathways were rapidly evolving, the actual art of Chemistry has not evolved. The Chemistry student still works with Erlenmeyer flasks, round-bottom flasks, and reflux condensers. The modern chemistry research and teaching laboratories would be instantly recognisable to a chemist from a century ago. Figure 10.1 compares the most modern laboratory in the world, the Edison laboratory in 1910 (ACS, 2025) with our current teaching and research laboratory at the University of Johannesburg. Both feature laboratory benches, glass bottles, and other familiar elements, capturing the enduring essence of laboratory environments across generations.

While the actual chemical synthesis procedures have remained largely unchanged, there has been a steady development of analytical equipment. In parallel, other related disciplines, such as Biochemistry, have been evolving to include initially standardised plasticware, which resulted in the opportunity to automate laboratory tasks. This automation of laboratory tasks proved to be rather slow in chemistry because of the Chemistry laboratory being an inherently heterogeneous environment.

In the last couple of decades, automation and robotics have developed to be used in chemistry research laboratories. Here we are using the term automation for equipment, performing



**Figure 10.1:** (a) Thomas Edison's laboratory from around 1910 (ACS, 2025). (b) a photo of a research laboratory at the University of Johannesburg, 2025 (photo credit: R. Meijboom).

a task without a feedback loop, and robotics for equipment with sensors and feedback loops. Thus, an auto-sampler would be termed automation, and a line-following "robot" would be called robotics. When the feedback loop involves artificial intelligence (AI), we start moving towards so-called self-driving laboratories (also called self-optimising reactors).

Self-driving laboratories are autonomous experimental systems that have the potential to accelerate the discovery of key breakthroughs such as clean energy, energy storage, drug discovery, and new materials (Seifrid *et al.*, 2022a). Automated, robotic, and self-driving laboratories have the potential to improve reproducibility and increase researcher productivity by automating repetitive manual tasks such as liquid handling and powder dispensing. However, they require scientists to learn new skills related to the building, modifying, and maintaining of robotic systems. These systems consist of both hardware (i.e., robotic arms, liquid dispensers) and software (i.e., firmware, optimisation algorithms, data infrastructure). By automating repetitive and tedious manual tasks, scientists can focus on higher-level cognitive tasks such as formulating a hypothesis, data interpretation, and so forth (Seifrid *et al.*, 2022b).

The transition from automation, via robotics, to self-driving laboratories is a relatively smooth and straight path. An automated task, namely liquid handling, can be enhanced by integrating sensors, such as a camera. When a liquid handler is

used for crystallisation experiments, several solvent mixtures are used. An additional camera could optimise the liquid handling and, for example, alert the researcher that crystals are being formed. Finally, using machine vision and an optimisation algorithm, the same set-up initially used for liquid handling can now self-optimise the crystallisation conditions. This is crucial, as some of the examples that follow are not robotic or self-optimising yet, but have the potential to be a base-automated system, which can be developed into a self-optimising system. From here on, for the sake of clarity, we will be using the term "robotic systems" only.

New skills (for Chemistry students), including AI, data analysis, and the supervision of automated experiments, will be required to design, build, and operate chemical robotic systems. State-of-the-art robotics, while offering cutting-edge capabilities, can have a steep learning curve and incur significant expenses should anything go wrong. The low-cost (or frugal) equivalent presents a low-risk environment for education and can offer invaluable experience to drive the high-cost equivalent. Low-cost robotics creates an educational environment for experiential learning for students with limited robotics and programming experience. By making robotics affordable and easier to access, they can be introduced into the undergraduate curriculum at an early stage.

## 2. State of the Art Robotics in Chemistry

Only recently has a range of robotic systems been described in the Chemistry literature. The initial systems described were derived from the use in laboratories with enormous amounts of resources. For example, the initial examples of liquid handling robotics were developed for the pharmaceutical industry to screen potential pharmaceutical compounds. Later, other robotic systems entered the market, but these were still prohibitively expensive. The initial automated synthesis systems would cost millions of rand to purchase (e.g., the Chemspeed Swing), and there are very few of these systems in Africa.

Because robotics in Chemistry is an interdisciplinary approach to Chemistry, very few research groups worldwide have experience working on the subject. Only recently, some

research groups have employed mechatronics specialists to assist with building robotic systems. This has now resulted in some standardised approaches, which will be described in this chapter. For our research group (Alimi *et al.*, 2022; Nel *et al.*, 2022) to catch up, however, we will need to build this experience for ourselves. This chapter will provide a guideline for developing this particular skill set for chemists, and also describes part of the experience of one research group at the University of Johannesburg trying to develop robotics in Chemistry.

The majority of current systems are rather expensive because they rely on expensive robotic components as a starting point, making them inaccessible to research institutions. These robotic systems can be separated into several categories. The first category could be termed "synthesis machines". This category includes "The Machine" developed by the Burke group (Li *et al.*, 2015). Another example of a synthesis machine is the "Chemputer" from the Cronin group, a commercial offering from Chemspeed Technologies used to automate synthesis (Steiner *et al.*, 2019; Angelone *et al.*, 2021; Bornemann-Pfeiffer *et al.*, 2021). "The Machine" from the Burke group relies on many commercial syringe pumps and selection valves, making this a rather expensive piece of equipment. Similarly, while the "Chemputer" from the Cronin group is a do it yourself (DIY) solution, it can be quite costly to implement. The "Chemputer" has custom three-dimensional (3D) printed parts and low-level electronic components such as syringe pumps. It also interfaces with existing chemistry instruments such as stirrer-hotplates, rotary evaporators, flow reactors, and in-line spectrometers. This combined collection can perform automated organic synthesis and characterisation.

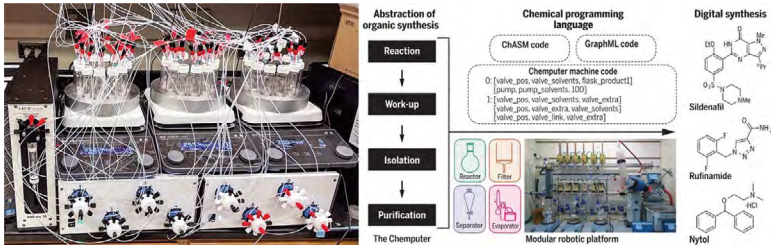



**Figure 10.2:** (a) "The Machine", and (b) the "Chemputer".

The second group of state-of-the-art robotics could be termed stationary robot arms and moving robot arms. These robotic systems typically use commercial robot arms, which are modified to perform Chemistry. The arms are generally used to mimic a human performing several actions (Roberts *et al.*, 2025). The example shown in Figure 10.3 from the Hein research group features a Kinova Gen3 robot arm equipped with a gripper and vision system that costs approximately R650k. Similarly, a robotic arm can be mobile, as observed in the example from the Cooper group (Burger *et al.*, 2020). The mobile arm would perform Chemistry similar to how a human would perform Chemistry. This example uses a Kuka robotic arm (approximately R650k) and a Kuka mobile robot (starting price ~R700k).

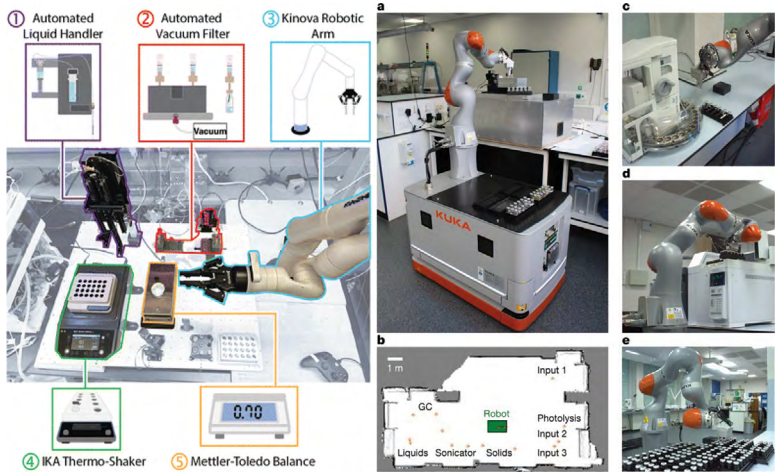



**Figure 10.3:** (a) A stationary robot arm (Roberts *et al.*, 2025), and (b) a mobile robotic chemist (Burger *et al.*, 2020).

The third group of robotics appears to be more affordable than the previous models discussed. This group could be classified as "liquid handling robotics" and includes the various examples of liquid handling in Biochemistry applications. A typical commercial liquid handler offered by the Hamilton company would cost approximately R350k. The price of liquid handling robotics has decreased significantly since Open-Source hardware companies like OpenTrons were founded in 2014. The first product from OpenTrons, the OT1, was funded as a Kickstarter campaign in 2015 and was

released for $2,000 (~R35k). While the OpenTrons costs significantly less than any other market offering, this would still be too expensive for a teaching laboratory in a resource-constricted environment.

Liquid handling robotics can be built at very low costs and would enable Biochemistry students to streamline their experimental workflows and facilitate high-throughput experimentation in Chemistry. Especially, high-throughput experimentation is a relatively new concept in Chemistry, and relatively few laboratories use this for research. The relatively low cost of liquid handling robotics, once built in-house, could result in using this type of robotics in the teaching environment. In addition, liquid handling robotics could open the door to machine learning and self-driving laboratories, as we will discuss later.

## 3. Frugal Twins – Necessary Skills

Chemistry is moving rapidly in the direction of what is currently called Digital Chemistry. Digital Chemistry can be described as the coming together of several subdisciplines in Chemistry, such as automation, robotics, "hacking" data science, flow chemistry, coding, and the use of Statistical Design of Experiments and AI. When we combine robotics and AI, we could end up with the so-called self-driving laboratories. Researchers, however, will be responsible by building these laboratories themselves. Similarly, these robotic set-ups will need to be built for education, but now at an increasingly diminishing cost.

To build a frugal twin of the afore-mentioned robotic systems, several skills need to be acquired by the chemist. Almost all examples that will be presented require some level of "maker" skills. Thus, computer-aided design (CAD) of parts is necessary to build your own parts. The CAD must then be 3D-printed and combined with off-the-shelf hardware. Finally, a foundation knowledge of electronics, such as Arduino, and coding is required.

Equally important is access to a maker space or an ecosystem containing 3D printers, laser cutters, a soldering station, and ample electronics to build these robotic systems. For example, a simple syringe pump is at the heart of several robotic systems. For a researcher or student to build a syringe pump, specific steps need to be taken:

1. Design the syringe pump in CAD software (or find a design online).
2. Slice the design using the right slicer software.
3. 3D-print the necessary parts on a 3D printer.
4. Purchase the required parts, such as linear bearings, end-stops, stepper motors, and various nuts and bolts.
5. Build the syringe pump from the 3D-printed and purchased parts.
6. Connect the stepper motor to an Arduino board, via a stepper motor shield, and connect this up to the right power supply.
7. Write the firmware code in the Arduino IDE and flash this to the Arduino board.
8. Write the required code in Python to drive the syringe pump.

Thus, to produce a simple syringe pump (Figure 10.4) (Github, 2025a), rudimentary knowledge of a range of skills is a prerequisite, including CAD, electronics, 3D printing, C++ coding (for Arduino), and Python coding. Furthermore, especially with the presented example here, an understanding of the larger ecosystem of modular parts and modular code libraries is also required. However, the typical undergraduate Chemistry curriculum overlooks these crucial skills. To properly educate our students in robotic chemistry, the prerequisite skills for robotics must be integrated into the standard curriculum.

Several examples of frugal robotics projects make use of code libraries developed by the Cronin group. The Cronin group, in Glasgow, UK, has been pioneering robotics in chemistry for over a decade. The Cronin group set out to have every part standardised and modular. For example, they developed a standard, modular linear actuator centred around a linear guide rail and a stepper motor. This actuator is used as the basis of a modular syringe pump. Another example is the use of a standardised Geneva wheel as an autosampler and a high-throughput reaction system. Finally, the afore-mentioned "Chemputer" (Figure 10.2b) uses standardised syringe pumps, and selection valves powered via a Power-over-Ethernet hub and run by the software described below.

As a result of standardisation, the modular syringe driver presented in Figure 10.4 was designed. With this modular

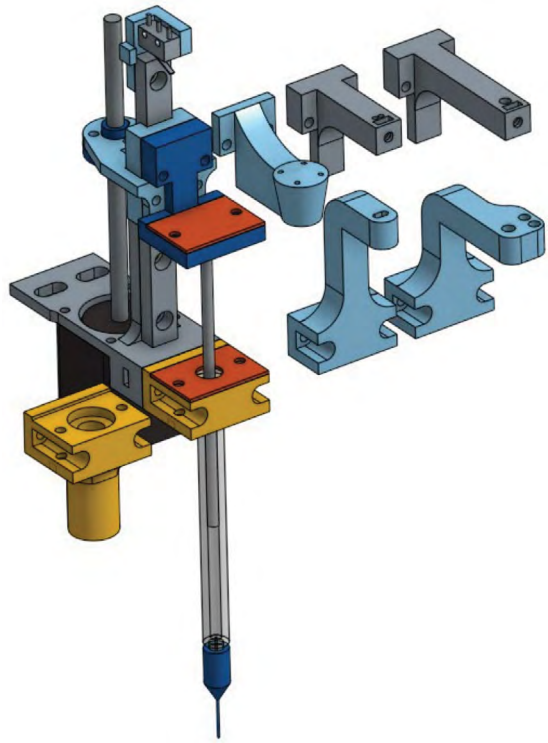


**Figure 10.4:** Modular syringe pump (Github, 2025a).

syringe pump, a standard software library called Arduino CommandTools was written (Github, 2025b). This library, when coupled with Arduino CommandHandler (Github, 2025c), ensures communication over the serial port of the Arduino. The function of this library is similar to the function of the better-known Firmata library: being able to give commands to the Arduino using serial communication. Given the substantial number of modules, this library ensures that proper communication with the Arduino can take place. However, communication with computers requires a range of libraries. Therefore, the group wrote the Commanduino library in Python to handle the computer side of robotics (Github, 2025d). In addition, a large library was written in Python by the Cronin group to address normal labware (Github, 2025e) including Tricontinent pumps, stirrer hotplates, rotary

evaporators, overhead stirrers as well as sensors such as NMR machines, UV-vis spectrometers, etc.

When looking at educational robotics as a frugal twin for state-of-the-art robotics, an additional skill set becomes clear. Most educational robots use Raspberry Pi computers, running a Linux distribution. Under Linux, typically, the Robotic Operating System is installed, as well as Python's OpenCV (Hiwonder, 2025a), a library to handle many camera functions. For several of the examples of frugal robotics, we used a headless Raspberry Pi, running Linux connected to the Arduino board or a syringe pump.

## 4. Frugal Synthesis Machines

### 4.1. Peristatic Pump-based

Preliminary evidence acquired from a low-cost robotic system can serve as proof-of-concept for subsequent justification of funding for more capable high-cost robotics. The low-cost robotic system may have lower accuracy and reliability, but it provides sufficient evidence for the proposed research. In addition, building low-cost robotic systems provides a learning opportunity for the researcher. One example of a low-cost robotic system that can be used to teach transferable skills to students is the MIK-I, reported as a frugal synthesis machine (Flores-Ortiz *et al.,* 2023). The purpose of the researchers was to build "The Machine", but to show proof-of-concept, they built MIK-I. The main purpose was to familiarise the researchers with automated synthesis platforms. To evaluate the usefulness of MIK-I, the researchers successfully performed a range of C-C bond formation reactions widely used in organic chemistry in an automated fashion (Figure 10.5a).

The MIK-I platform is a robotic cocktail mixer, where liquids can be mixed as desired. The MIK-I is built from peristaltic pumps and a Raspberry Pi. The setup is similar to the Cronin group's "Twitterbot" (Figure 10.5b) (Caramelli *et al.,* 2018), which consists of peristaltic pumps, driven by a PCDuino3 board – a combination of an Arduino board

and a Raspberry Pi board. The Cronin group used these set-ups for the collaborative investigation of azo-dye space, as well as following a chemical oscillator based on the Belousov–Zhabotinsky (BZ) reaction. The paper by the Cronin group (Caramelli *et al.*, 2018) further describes the collaborative search of chemical space for the evaluation of the reproducibility of a complex cluster, a known tungsten polyoxometalate (POM) cluster. These papers describe very low-cost robotic systems that are almost identical but can be used as an introduction to robotic chemistry.

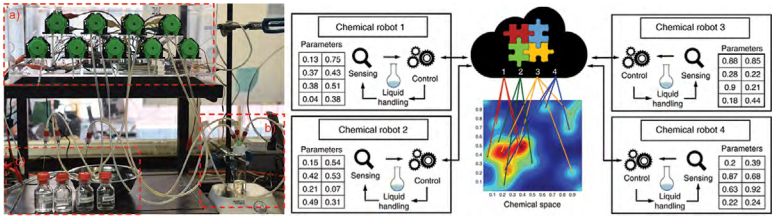



**Figure 10.5:** (A) MIK-I, a low-cost automated synthesis platform. Peristaltic pumps (a) are controlled by a Raspberry Pi. Also shown are the synthesis reactor (b), and reagent bottles (c). (B) The networked robotic systems are performing a collaborative search through chemical space.

Using lower-cost robotics facilitates the parallelisation of research campaigns while also democratising access to cutting-edge research tools. This means that geographically distant labs can build clones of the robot. These robots can then network and execute high-throughput and parallel reactions to evaluate various reaction parameters in a low-cost manner. The system is easily scalable, allowing researchers to add more robots as needed, similar to adding more cores to a central processing unit (CPU).

At the University of Johannesburg, we built several of these simple robotic systems from off-the-shelf, low-cost, peristaltic pumps and an Arduino Uno board (Moeng, 2025). After our initial success with more complex systems, the author realised that these were too difficult as an introduction to robotic chemistry. As a result, the author had new students in the field build a

"cocktail robotic" system as a first system to become familiar with robotics, coding, etc. These systems were used to reproduce the search of the azo-dye space as proof of principle. The robotic systems were then used to synthesise shaped silver nanoparticles. Currently, these peristaltic pump-based systems are part of an educational drive to teach new students how to build and run robotic set-ups.

When the final product is aimed at being a self-driving laboratory, there is one excellent example in the literature that should be mentioned here. This is relevant as the code could be potentially reused for any of the azo-dye examples that we have seen and will continue to see. As a straightforward demonstration for self-driving laboratories, Baird and Sparks developed a colour-matching self-driving lab as a minimum working example (Baird & Sparks, 2022). Here, the user can pick a colour, and the robot will use a red, green, and blue light-emitting diode (RGB-LED) to match the colour. Despite its simplicity, this example efficiently demonstrates the idea of a self-driving laboratory. This example also offers proof of principle for concepts such as the creation of a network of distant experiments and the implementation of various advanced optimisation strategies. Several tutorials and examples are provided in the documentation. For instance, examples for traditional Design of Experiments versus Bayesian optimisation are given, as well as multi-objective optimisation examples and "human in the loop" examples. Other examples of several machines working collaboratively towards a solution are also provided. Most of these examples can be found on the GitHub page for the project (Github, 2025f).

Baird and Sparks explored extensions of their minimum working example by expanding the modular software and hardware components. The platform was extended to a liquid-based colour-matching task, which uses the example of mixing red, yellow, and blue food colouring dyes (Figure 10.6) (Baird, 2023). It does not require much imagination to expand this minimal working prototype and expand this with more peristaltic pumps to investigate the azo-dye space.

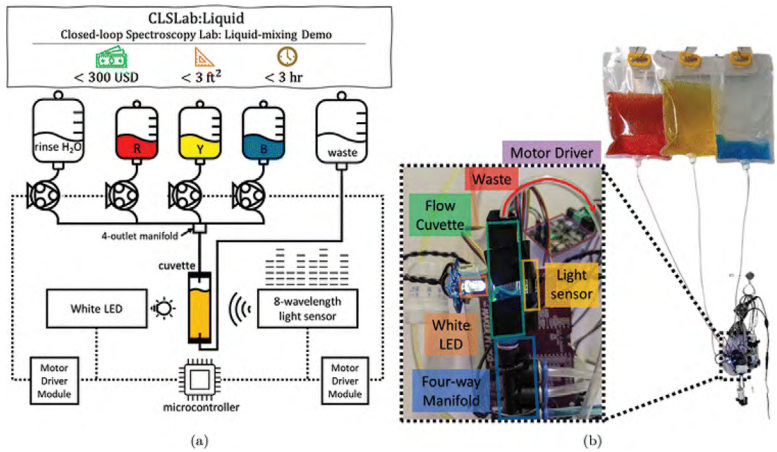



**Figure 10.6:** A simple self-driving laboratory using peristaltic pumps for mixing food colouring dyes in a cuvette.

## 4.2. Syringe Pump-based

While off-the-shelf peristaltic pumps are low-cost, they are not precise and need regular calibration to work satisfactorily. It was noted by the Cronin group that the afore-mentioned collaborative robots (a.k.a. Twitterbots) were low-cost, but that the low-cost hardware resulted in significant frustration for the researchers. The Cronin group subsequently published their Chemputer (Figure 10.2b), consisting of syringe pumps, selection valves, reactors, and so forth. While this was an expensive set-up to build and is financially out of reach for low-resourced environments, the Chemputer can be used as an inspiration for lower-cost robots.

Inspired by the Chemputer, Vadivel *et al.,* published the *Mostly 3D printed chemical synthesis robot* in 2022 (Vadivel *et al.*, 2022). They called the robot "the syringebot". This robot consists of syringe pumps, two-way selection valves, a stirrer hotplate, a temperature probe, and a pH probe. They decided to assemble a liquid-handling robot able to control a heater-stirrer and expanded it with modules for pH and redox electrodes. The unit is controlled by a Raspberry Pi 3 module and a Python program that renders the interfacing easier. Unfortunately, the only example of Chemistry reported with the syringebot was a pH titration.

However, this set-up has enormous potential to be expanded for low-cost robotics in the undergraduate curriculum.

Kuwahara *et al.,* developed their "FLUID" robotic set-up inspired by the syringebot (Kuwahara *et al.*, 2025). FLUID is a robot designed to streamline the control and synthesis of liquid compounds, enhancing efficiency for human operators. FLUID consists of hardware and software. On the hardware side, FLUID consists of four independent syringe modules, each capable of aspirating or injecting liquid through three pathways controlled by two valves. Servo motors manage valve positioning, while a stepper motor controls the syringe plunger for precise liquid movement. Each unit includes an end-stop limit sensor that triggers when the syringe reaches its maximum fill position. The motors, servos, and sensors in each module connect to bespoke microcontroller boards located at the rear of the robot, which is powered by a supply converting standard wall outlet power to the necessary 5 V and 12 V outputs. The microcontroller firmware awaits commands from a connected computer or single-board computer via a USB serial port. This robot was used to prepare Co-Ni oxides (Figure 10.7).

At the University of Johannesburg, we designed a demonstration unit for automated reactions using a Tricontinent syringe pump with a six-way selection valve (Nel *et al.,* 2022). This set-up was used for the automated synthesis of aspirin in a batch reactor. The demonstrated synthesis used a programmable syringe pump with a six-way selection valve, a computer-controlled stirrer hot plate with a temperature probe, several reagent bottles, and a computer. We have used both a laptop and a Raspberry Pi to execute the automated synthesis of aspirin. The reaction was performed in a round-bottom flask with a condenser. Teflon tubing connected the syringe pump to the reactor as well as to the reagent flasks. The complete set-up was contained using 3D-printed tiles (Figure 10.8).

The reaction was demonstrated to 31 third-year Chemistry students. Despite being interested in the digital synthesis approach, most students felt that they were not ready for this

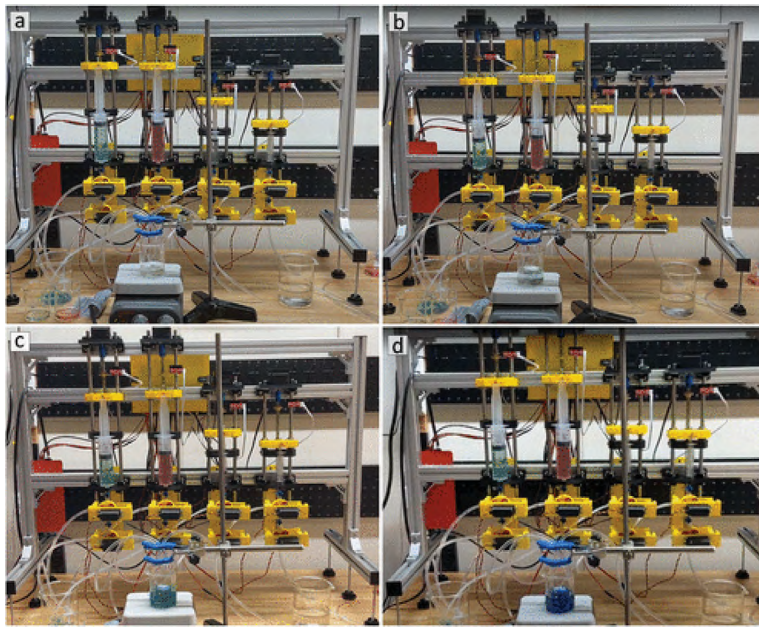



**Figure 10.7:** Process of coprecipitation of Co and Ni with NaOH using FLUID to synthesise Ni–Co oxides. (a) Before running the robot, (b) releasing Ni(NO3)2 solution, (c) releasing Co(NO3)2 solution, and (d) adding NaOH solution.

level of Chemistry, mainly because of a lack of coding in the classical undergraduate curriculum for Chemistry. Based on the Chemputer principle, Nel, at the University of Johannesburg, developed a low-cost syringe pump with a ten-way selection valve robotic setup (Nel *et al.*, 2021). These low-cost syringe pumps and selection valves were connected to an Arduino Mega 2560 with a RAMPS1.4 shield running the Arduino CommandHandler (Github, 2025c) and Arduino CommandTools (Github, 2025b). The Arduino Mega was connected via USB to a headless Raspberry Pi with an interfaced Raspberry Pi camera. The Raspberry Pi was running the Python library Commanduino (Github, 2025d). This flexible set-up was used to initially repeat the synthesis of aspirin as demonstrated previously using a

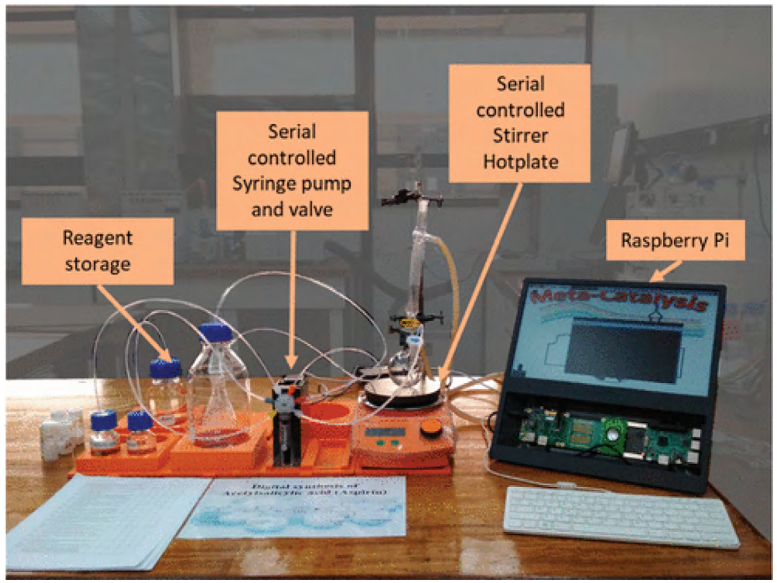
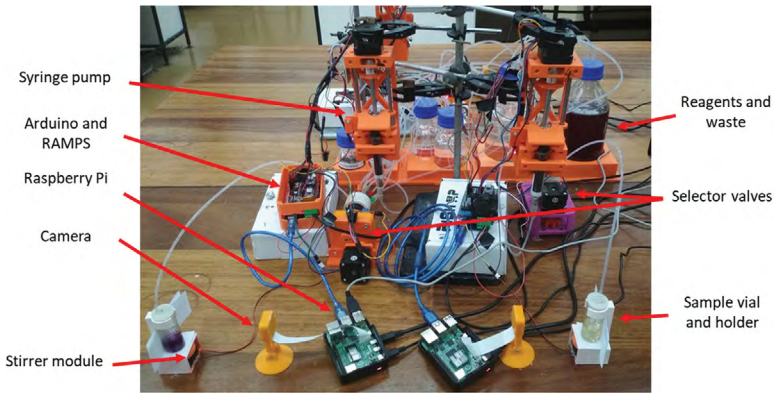
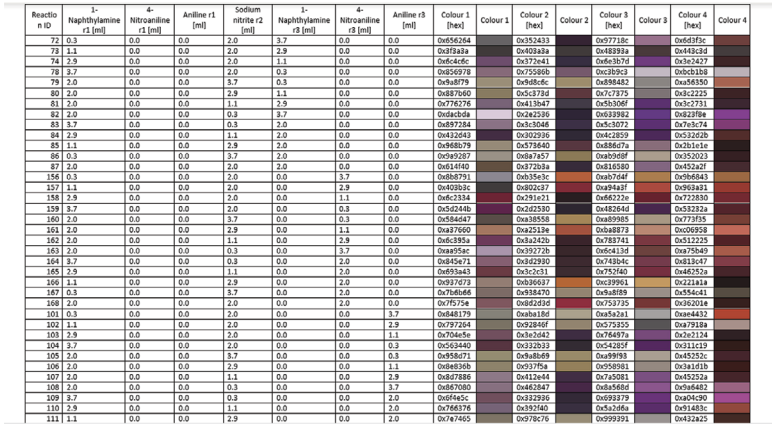



**Figure 10.8:** The automated synthesis of aspirin (Nel *et al.*, 2022).




Tricontinent pump (Nel *et al.*, 2022). Subsequently, three of these robots were connected via Wi-Fi to a distant Raspberry Pi, and the three set-ups ran 107 different azo-dye reactions in less than 40 hours (Figure 10.9).



| Reaction ID | 1-Naphthylamine r1 [ml] | 4-Nitroaniline r1 [ml] | Aniline r1 [ml] | Sodium nitrite r2 [ml] | 1-Naphthylamine r3 [ml] | 4-Nitroaniline r3 [ml] | Aniline r3 [ml] | Colour 1 [hex] | Colour 1 | Colour 2 [hex] | Colour 2 | Colour 3 [hex] | Colour 3 | Colour 4 [hex] | Colour 4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 72 | 0.3 | 0.0 | 0.0 | 2.0 | 3.7 | 0.0 | 0.0 | 0x656264 | | 0x352433 | | 0x97718c | | 0x6d3f3c | |
| 73 | 1.1 | 0.0 | 0.0 | 2.0 | 2.9 | 0.0 | 0.0 | 0x2f3a8a | | 0x403a3a | | 0x48393a | | 0x443c2d | |
| 74 | 2.9 | 0.0 | 0.0 | 2.0 | 1.1 | 0.0 | 0.0 | 0x6c4c6c | | 0x372e41 | | 0x6e3b7d | | 0x3e2427 | |
| 78 | 3.7 | 0.0 | 0.0 | 2.0 | 0.3 | 0.0 | 0.0 | 0x856978 | | 0x75586b | | 0xc3b9c3 | | 0xbcb1b8 | |
| 79 | 2.0 | 0.0 | 0.0 | 3.7 | 0.3 | 0.0 | 0.0 | 0x9d8c6c | | 0x988482 | | 0xa58350 | | | |
| 80 | 2.0 | 0.0 | 0.0 | 2.9 | 1.1 | 0.0 | 0.0 | 0x807d60 | | 0x5c378d | | 0x7c7375 | | 0x3c2225 | |
| 81 | 2.0 | 0.0 | 0.0 | 1.1 | 2.9 | 0.0 | 0.0 | 0x776276 | | 0x413b47 | | 0x5b306f | | 0x3c2731 | |
| 82 | 2.0 | 0.0 | 0.0 | 0.3 | 3.7 | 0.0 | 0.0 | 0xdacbda | | 0x2e2536 | | 0x633982 | | 0x823f8e | |
| 83 | 3.7 | 0.0 | 0.0 | 0.3 | 2.0 | 0.0 | 0.0 | 0x897284 | | 0x3c3046 | | 0x5c3072 | | 0x7e3c74 | |
| 84 | 2.9 | 0.0 | 0.0 | 1.1 | 2.0 | 0.0 | 0.0 | 0x432643 | | 0x302936 | | 0x422859 | | 0x32626b | |
| 85 | 1.1 | 0.0 | 0.0 | 2.9 | 2.0 | 0.0 | 0.0 | 0x968b79 | | 0x573640 | | 0x886d7a | | 0x2b1e1e | |
| 86 | 0.3 | 0.0 | 0.0 | 3.7 | 2.0 | 0.0 | 0.0 | 0x9a9287 | | 0x8a7a57 | | 0xab9d8f | | 0x352023 | |
| 87 | 2.0 | 0.0 | 0.0 | 2.0 | 2.0 | 0.0 | 0.0 | 0x614f40 | | 0x372b3a | | 0x816580 | | 0x452a2f | |
| 156 | 0.3 | 0.0 | 0.0 | 2.0 | 0.0 | 3.7 | 0.0 | 0x8b8791 | | 0xb35e3c | | 0xab764f | | 0x9b6843 | |
| 157 | 1.1 | 0.0 | 0.0 | 2.0 | 0.0 | 2.9 | 0.0 | 0x403b3c | | 0x802c37 | | 0xa94a3f | | 0x903a31 | |
| 158 | 2.9 | 0.0 | 0.0 | 2.0 | 0.0 | 1.1 | 0.0 | 0x6c2334 | | 0x291e21 | | 0x66222e | | 0x722830 | |
| 159 | 3.7 | 0.0 | 0.0 | 2.0 | 0.0 | 0.3 | 0.0 | 0x5d244b | | 0x2d2530 | | 0x48264d | | 0x53282a | |
| 160 | 2.0 | 0.0 | 0.0 | 3.7 | 0.0 | 0.3 | 0.0 | 0x564447 | | 0xa38558 | | 0xab8985 | | 0x773f35 | |
| 161 | 2.0 | 0.0 | 0.0 | 2.9 | 0.0 | 1.1 | 0.0 | 0xa27660 | | 0xa2513e | | 0xba8873 | | 0xc06958 | |
| 162 | 2.0 | 0.0 | 0.0 | 1.1 | 0.0 | 2.9 | 0.0 | 0x6c395a | | 0x3a242b | | 0x783741 | | 0x512225 | |
| 163 | 2.0 | 0.0 | 0.0 | 0.3 | 0.0 | 3.7 | 0.0 | 0xae95ac | | 0x39272b | | 0x6c413d | | 0xa75b49 | |
| 164 | 3.7 | 0.0 | 0.0 | 0.3 | 0.0 | 2.0 | 0.0 | 0x845e71 | | 0x3d2930 | | 0x743b4c | | 0x813c47 | |
| 165 | 2.9 | 0.0 | 0.0 | 1.1 | 0.0 | 2.0 | 0.0 | 0x693a43 | | 0x3c2c31 | | 0x75254d | | 0x44252a | |
| 166 | 1.1 | 0.0 | 0.0 | 2.9 | 0.0 | 2.0 | 0.0 | 0x937d73 | | 0xb36637 | | 0xc39961 | | 0x221a1a | |
| 167 | 0.3 | 0.0 | 0.0 | 3.7 | 0.0 | 2.0 | 0.0 | 0x7b6b66 | | 0x938470 | | 0x9a8f89 | | 0x554c41 | |
| 168 | 2.0 | 0.0 | 0.0 | 2.0 | 0.0 | 2.0 | 0.0 | 0x7f575e | | 0x8d2d3d | | 0x753735 | | 0x362014 | |
| 101 | 0.3 | 0.0 | 0.0 | 2.0 | 0.0 | 3.7 | 0.0 | 0x848179 | | 0xaba18d | | 0xa5a2a1 | | 0xae4432 | |
| 102 | 1.1 | 0.0 | 0.0 | 2.0 | 0.0 | 2.9 | 0.0 | 0x797264 | | 0x92846f | | 0x575355 | | 0xa7918a | |
| 103 | 2.9 | 0.0 | 0.0 | 2.0 | 0.0 | 1.1 | 0.0 | 0x704e5e | | 0x3e2d42 | | 0x76497a | | 0x2e2124 | |
| 104 | 3.7 | 0.0 | 0.0 | 2.0 | 0.0 | 0.3 | 0.0 | 0x563440 | | 0x332b33 | | 0x5420bf | | 0x311c19 | |
| 105 | 2.0 | 0.0 | 0.0 | 3.7 | 0.0 | 0.3 | 0.0 | 0x958d71 | | 0x8a8b69 | | 0xa99f93 | | 0x45252c | |
| 106 | 2.0 | 0.0 | 0.0 | 2.9 | 0.0 | 0.0 | 1.1 | 0x8e836b | | 0x93ff5a | | 0x958981 | | 0x3a1d1b | |
| 107 | 2.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 2.9 | 0x8d7886 | | 0x412e44 | | 0x7a5081 | | 0x45252a | |
| 108 | 2.0 | 0.0 | 0.0 | 0.3 | 0.0 | 0.0 | 3.7 | 0x867080 | | 0x462847 | | 0x8a568d | | 0x9a6482 | |
| 109 | 3.7 | 0.0 | 0.0 | 0.3 | 0.0 | 0.0 | 2.0 | 0x6f4e5c | | 0x322936 | | 0x693379 | | 0xa04c90 | |
| 110 | 2.9 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 2.0 | 0x766376 | | 0x392f40 | | 0x5a2d6a | | 0x91483c | |
| 111 | 1.1 | 0.0 | 0.0 | 2.9 | 0.0 | 0.0 | 2.0 | 0x7e7465 | | 0x978c76 | | 0x999391 | | 0x432a25 | |

**Figure 10.9:** The robotic setup by Nel at the University of Johannesburg (top) and the type of data collected by the setup (bottom) (Nel *et al.*, 2022).

## 4.3. Modular Wheel Platform

In 2020, the Cronin group published their first version of the so-called Modular Wheel Platform (Salley at al., 2020a). The Geneva wheel platform is capable of rotating 24 reactors using the Geneva mechanism and a stepper motor, which enables it to run 24 parallel reactions. For every rotation, the necessary reagents are dispensed serially into a reactor with peristaltic pumps. Each reactor has a magnetic stirring module that stirs 24 reactions in parallel. In addition, the sampling and cleaning modules can move in x, y, and z directions along the platform frame, which enables in-line measurements, sample extraction, transfer between vials, and cleaning of reactors to prevent cross-contamination.

In subsequent variations, additional linear actuators to move pH probes into the reaction vials and syringe pumps were added (Figure 10.10) (Salley at el., 2020b). The complete set-up is compatible with the previously described firmware, software, and hardware ecology. The set-up runs on an Arduino Mega 2560 with a RAMPS1.4 shield. The firmware controlling the Arduino is the Arduino CommandHandler and Arduino CommandTools. The Arduino is connected to a computer via USB, and the computer runs Python using the Commanduino library (Figure 10.11).

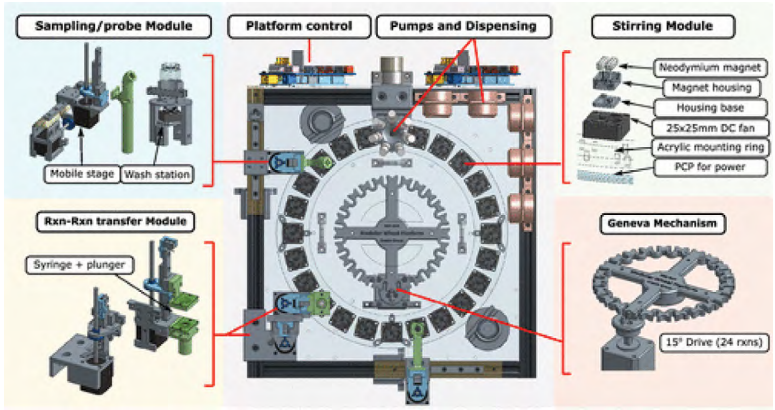



**Figure 10.10:** The modular wheel platform, equipped with several modules, including peristaltic pumps and syringe pumps (Salley at el., 2020b).

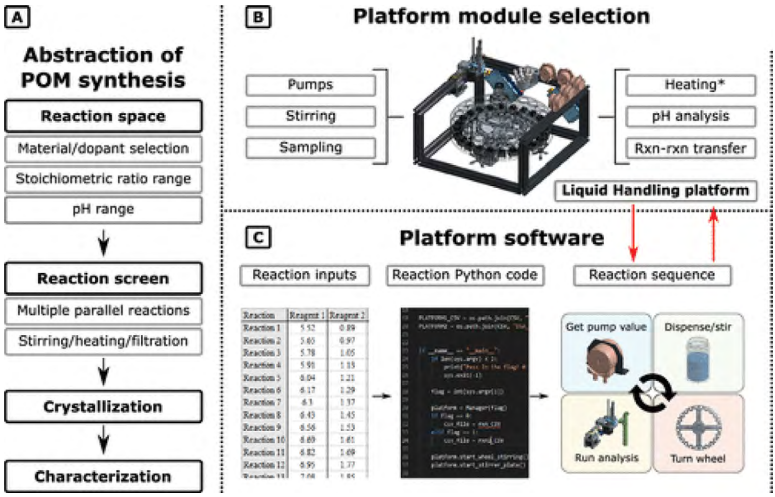



**Figure 10.11:** (A) Abstraction of inorganic/polyoxometalate synthesis. (B) The Modular Wheel Platform is built using modules selected by the user to perform the required operation. (C) Reaction inputs via CSV/JSON files communicate with the hardware from an executable synthesis code, all handled by software (Salley at el., 2020b).

## 5. Stationary Robot Arms and Moving Robot Arms

As described before, a range of rather expensive stationary and mobile robot arms are reported in the literature (Burger *et al.*, 2020; Roberts *et al.*, 2025). These robot arms are out of reach for most research laboratories, let alone for educational purposes. However, the principle of working with these robot arms can still be taught using "toy" robot arms. Currently, there is a large assortment of robot arms for the educational market that can be used in the laboratory. The advantage of using these educational robot arms is that the student becomes familiar with the underlying software and firmware structure.

For example, the well-known Boston Dynamics robot dog Spot (Figure 10.12a) has a smaller toy cousin produced by the Shenzhen company Hiwonder called the Hiwonder MechDog (Hiwonder, 2025b). The Hiwonder MechDog is an open-source robot with computer vision and voice activation. While Spot by Boston Dynamics could easily cost up to R1m, you could have the MechDog for as little as R5k. However, the price could go down significantly if you simply 3D-print the so-called "Spot micro" – a 3D-printed, open source, DIY variation of Spot (Autodesk Instructables, 2025). Obviously, the capacity of the Boston Dynamics robot dog is completely different from its toy variation or the 3D-printed variation. However, the toy variation can still teach students how to control a robot dog.

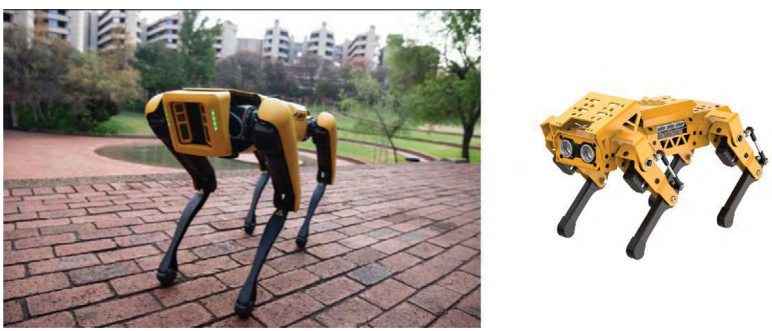


**Figure 10.12:** a) Spot from Boston Dynamics at the University of Johannesburg (University of Johannesburg, 2021), and b) its smaller cousin, the Hiwonder MechDog (Hiwonder, 2025b).

In a similar way, expensive mobile and stationary robot arms can be replaced by their "toy" equivalents to teach students how the software stack works. These "toy" robot arms are typically quite sturdy and could perform a range of Chemistry when coded properly. At the University of Johannesburg, we are currently investigating the use of the Hiwonder ArmPi Pro as a potential mobile robotic arm in Chemistry.

The ArmPi Pro is driven by a Raspberry Pi computer and is equipped with computer vision. This robotic system runs on a Linux variation, with the Robotic Operating System (ROS) in a Docker container. It also runs OpenCV, the Python computer vision library, and utilises AI vision. It can work with AI facial recognition, colour recognition, and April Tags. Thus, students can learn, by using this robotic system, about setting up a Linux environment. After that, they can set up container software (Docker), ensuring that if something goes wrong with the software, it does not influence the complete system. Finally, students can learn about computer vision while using this simple robotic system. Thus, a range of activities can be designed around these "toy" robotic arms for the undergraduate teaching laboratory.

## 6. Liquid Handling Robotics

Liquid handling robotics is used extensively in the Life Sciences. However, for some reason, they are not as widely used in the domain of Chemistry. A number of low-cost solutions have been reported in the literature, with a LEGO®-based liquid handling robotic setup being one of the more interesting and low-cost ones (Gerber *et al.,* 2017). This LEGO®-based liquid handling robot was used in outreach projects teaching simple automated dilutions (Figure 10.13a). The authors continued developing this robotic set-up to form a laser-cut variation, which is even lower-cost than the original LEGO®-based liquid handling robotic setup (Li *et al.,* 2022). The updated liquid handling robotic platform was coded by Snap4Arduino, a graphical programming language.

Based on the Lego-based liquid handling robot, Saar *et al.,* (2022) developed the LEGOLAS platform - a LEGO®-based Low-Cost Autonomous Science platform (Figure 10.13). LEGOLAS is an easy-to-use modular system based on modular toy parts,

3D-printed parts, Raspberry Pi components, and aluminium extrusions with a total cost of less than $300 (~R5k). The LEGOLAS platform was used to teach both undergraduate and postgraduate students machine learning courses. The robot kit was adapted for liquid handling and pH testing. The robot was also used for the aforementioned colour-matching using food colouring.

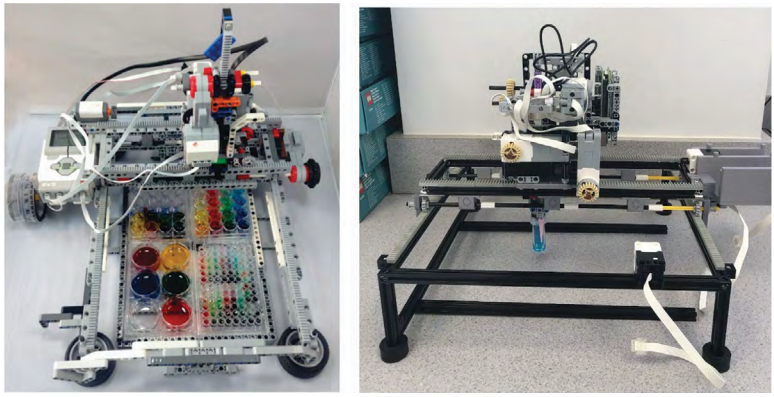


**Figure 10.13:** (A) The LEGO®-based liquid-handling robot, and (B) LEGOLAS version IV.

## 6.1. Jubilee System

The Jubilee platform was created by Vasquez *et al.*, at the University of Washington as a multi-tool changing fabrication platform (Vasquez *et al.*, 2020). The initial aim was to design a multi-head 3D printer and pen-plotter. This was extended to simple liquid handling through syringe pumps. The Jubilee system evolved from a modular tool-changing system that accommodates user-created tools and beds (Figure 10.14). The platform was extended for automated ultrasound applications in a workflow combining a liquid-handling robot and a plate spectrometer for the synthesis of CdSe nanodots (Politi *et al.*, 2023).

The Jubilee system can be built for a low price and offers a flexible approach to robotics. Current tools compatible with the Jubilee system are extruders for 3D printing, pens for pen-plotting, syringes for liquid transfer, as well as a USB camera. Several build plates are also available, including a plate for multi-well plates. The Jubilee system could develop into a self-driving laboratory if so desired.

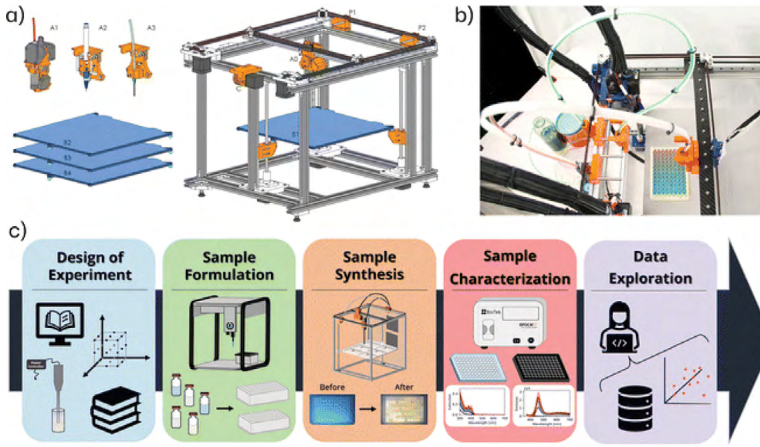



**Figure 10.14:** (a) The blueprint design of the Jubilee system which can equip modular multi-headed tools. (b) Example of the Jubilee system dispensing liquids into a 96-well plate. (c) The workflow of adapting Jubilee into the automated sono-chemical synthesis of nanocrystals (Politi *et al.*, 2023).

## 7. Teaching Chemical Robotics – A Proposed Initial Curriculum

For us to teach robotics in chemistry, a curriculum that utilises a low-cost robotics framework is required. Furthermore, streamlining and standardising procedures will help students to stay focused and avoid unnecessary complications. We have already standardised Arduino CommandHandler and Arduino CommandTools on the firmware modules, with the corresponding Python library Commanduino. Similarly, for the electronic components, we have standardised using an Arduino Mega 2560, and a RAMPS1.4 shield with the relevant stepper motor shields. However, our initial curriculum does not start with those standard components, as the learning curve is too steep. At present, we are teaching low-cost robotics by focusing first on simple Arduino coding, using well-known examples, such as "blink", using an Arduino Uno. Subsequently, we move to Python coding for Arduino, using the well-known Firmata communication protocol. Once students are comfortable with the Python-Firmata

coding, we start teaching the Arduino CommandHandler – Arduino CommandTools – Commanduino combination. This provides students with a range of skills and prepares them for simplified robotics.

The next step is to have the students build a "cocktail robotic" set-up using peristaltic pumps, an Arduino running CommandHandler and CommandTools, and a Raspberry Pi running the Commanduino and other Python libraries. This empowers the students with the skills for building a simple system and interfacing this system with other robots. At this stage, simple chemical reactions can be performed. Once students have mastered the set-up using peristaltic pumps and the various firmware (on Arduino) and software (Python) libraries, we can then familiarise them with syringe pumps, linear actuators, selection valves, and modular wheels. These are all stepper motor-based modular items used to control a complete robotic platform. We also discuss various sensors. While the students are familiarising themselves with syringe pumps, more details about 3D printing and laser cutting, with the CAD, are being taught in conjunction with additional electronics.

Once these automation tasks are understood by our students, we can move towards the use and implementation of self-driving laboratories. This will start to include machine learning in the curriculum. Some examples of low-cost self-driving laboratories were given throughout this chapter and could be used to "anchor" the machine learning for chemists' modules by combining learning by doing with Chemistry and machine learning.

Digital Chemistry is a relatively new paradigm in Chemistry and combines several sub-disciplines. The sub-disciplines in Digital Chemistry are related to "hacking" for chemists, automation, AI, data science, robotics, Statistical Design of Experiments, flow chemistry, high throughput chemistry, etc. Currently, these sub-disciplines are developing at an accelerated speed, and we need to teach components of each in our undergraduate and postgraduate teaching.

## 8. Conclusions and the Way Forward

For Chemistry in Africa to remain relevant, we need to adopt clever, low-cost strategies to teach our students the state-of-the-art technology. The author has illustrated several low-cost robotic systems that can easily be built with a minimum infrastructure of a decent computer and a low-cost 3D printer. Most of the effort with low-cost robotics is around the learning of various skills, such as rudimentary electronics, coding of Arduino boards, as well as Python modules. As educators in Africa, we need to change our curriculum to prepare our students for the world of tomorrow. Robotics is coming to Chemistry, and we have an excellent onboarding point at this moment to catch up with the state-of-the-art laboratories where robotic chemistry is being developed.

Another chapter in this volume discusses the use of 3D-printed flow chemistry modules for education. Here, we take the concept one step further, and have developed the idea of robotics, based on 3D -printed and off-the-shelf components. A rudimentary curriculum was also developed, teaching our students not only how to develop robot parts but also how to code them. The final part of this journey towards DIY robotics would be to take our robotic systems into virtual reality (VR). Several groups are currently taking their systems into virtual reality to teach their students how these systems work. For example, Figure 10.15 shows the VR variation of the "Chemputer", introduced in Figure 10.2 (Nature, 2025). All parts can be seen here: syringe pumps, selection valves, storage bottles, and a rotary evaporator.

This virtual reality environment can be physically coupled with robotic systems in a laboratory. Thus, a robot arm, for example, could mimic the movement of a human experimenter, and when the human rotates their hand to mimic pouring a liquid from a flask, the robot arm can do the same thing in the laboratory. Similarly, data can be depicted in the virtual environment as it is collected by the equipment in the laboratory. In Africa, we owe it to our students to keep up with the development of these systems and train our students for the world of tomorrow. We need to encourage staff and students to come up with cost-effective ways of teaching these skills. The skills needed by the chemist of tomorrow are significantly different from the skills being taught on a daily basis now.

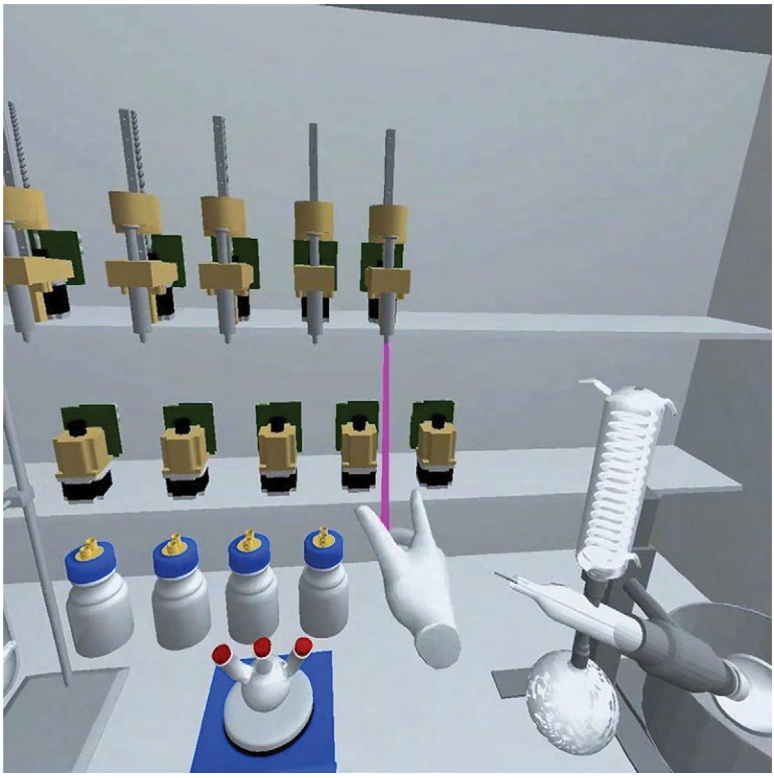


**Figure 10.15:** The VR variation of the "Chemputer" (Nature, 2025).

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Chapter 11

# From Introduction to Integration: Developing an Evidence-Based Implementation Framework for AI Virtual Tutors in Molecular Physiology Education

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## Abstract

AI-powered virtual tutors offer a transformative opportunity for Molecular Physiology education, but research on their implementation and effectiveness in higher education Science courses remains limited. This study aimed to develop an evidence-based implementation framework for integrating AI virtual tutors into Biochemistry modules, specifically focusing on Molecular Physiology. We analysed the implementation of an AI chatbot, evaluating its usage patterns, student satisfaction, and learning outcomes. A mixed-methods study was conducted in a third-year Molecular Physiology module (BIC03B3) with 43 students. The study integrated a structured two-hour "AI Chatbot Challenge" introduction session, immediate satisfaction assessment, and subsequent semester-long usage tracking. Students completed guided activities like concept clarification, self-assessment creation, and multilingual

explanation tasks. Student perceptions were assessed using a seven-item satisfaction survey after the introduction. Usage data were collected across temporal patterns, content themes, interaction purposes, and language preferences throughout the semester. Students reported remarkably high satisfaction across all measured dimensions (4.36-4.76/5.0), with self-assessment generation achieving the highest satisfaction (4.76/5.0), followed by psychological safety in asking sensitive questions (4.71/5.0). Usage analysis revealed that 84.9% of interactions focused on concept clarification, with peak engagement during evening study hours (18:00-19:00) and weekends. Content engagement concentrated on core Molecular Physiology topics, including signal transduction pathways (68 interactions), plasma membrane function (66 interactions), and immune system components (47 interactions). English dominated language usage (98.7%). The implementation and use of AI chatbots for Molecular Physiology education provide robust evidence for their effectiveness as virtual tutors in biochemistry modules. High satisfaction scores, sustained engagement patterns, and focused usage on concept clarification validate the pedagogical value of AI tutoring systems. This implementation framework demonstrates that a single intensive introduction session can establish lasting usage patterns, and AI tutors excel at creating psychologically safe learning environments and generating high-quality self-assessment materials.

**Keywords:** Educational technology, Higher education, Mixed-methods research, Molecular Physiology, Virtual tutoring.

## 1. Introduction

Molecular Physiology education presents unique pedagogical challenges because of the complex integration of molecular mechanisms with physiological processes. Students must master abstract biochemical concepts while understanding their application to whole-system physiology, creating substantial cognitive load and frequent misconceptions. Traditional lecture-based approaches often fail to provide the individualised support necessary for conceptual understanding, while limited instructor availability restricts opportunities for timely clarification of complex topics. Artificial intelligence

(AI)-powered virtual tutors offer a promising solution to these educational challenges. Recent research demonstrates that well-designed AI tutoring systems can achieve more than twice the learning gains of traditional active learning methods while providing 24/7 accessibility and personalised instruction. A randomised controlled trial at Harvard University involving 194 undergraduate Physics students found that a pedagogically designed AI tutor produced more than double the median learning gains compared to high-quality in-class active learning (effect sizes of 0.73–1.3 standard deviations), while requiring less time on task, and students reported greater engagement and motivation (Kestin *et al.*, 2025).

Despite growing evidence for AI tutoring effectiveness in Science, Technology, Engineering and Mathematics (STEM) education, limited research exists specifically addressing Molecular Physiology applications. The CIRCSIM-Tutor system, a natural language dialogue-based intelligent tutoring system for Cardiovascular Physiology, provides an instructive precedent: pre-test / post-test experiments with first-year medical students demonstrated that just one hour of use produced significant learning gains and improved problem-solving ability beyond what reading textual material alone could achieve (Woo *et al.*, 2006). More recently, a randomised controlled trial in medical education found that students trained with an AI tutor achieved higher Expertise Scores, while Objective Structured Assessment of Technical Skill (OSATS) ratings were comparable to those taught by expert surgeons (Fazlollahi *et al.*, 2022). Broader systematic reviews have mapped the expanding landscape of AI in STEM education, identifying intelligent tutoring systems as amongst the most prevalent applications across disciplines and documenting improvements in learning, motivation, and autonomy, though without aggregating quantitative effect sizes (Xu & Ouyang, 2022; Lin *et al.*, 2023). Despite these advances, the unique challenges of integrating molecular and physiological concepts require dedicated investigation.

This is particularly true for the South African higher education context, where structural challenges amplify the need for scalable, personalised learning support. South African universities serve linguistically diverse student populations, yet instruction in

the sciences is conducted almost exclusively in English, creating an additional cognitive burden for students learning complex content in what is often their second or third language. Simultaneously, resource constraints, including limited tutoring capacity, high student-to-lecturer ratios, and restricted access to academic support outside formal contact hours mean that students who fall behind in conceptually demanding modules have few avenues for remediation. AI-powered virtual tutors, therefore, offer a particularly compelling intervention in this context as they provide on-demand, individualised support that can operate at scale without requiring proportional increases in staffing. Furthermore, as language models continue to improve, AI models promise to ultimately offer effective explanations in students' home languages.

This study was conducted using LearnBridge, an in-house developed AI tutoring platform at the University of Johannesburg, a comprehensive South African institution. We investigated how students in a third-year Molecular Physiology module adopted and engaged with an AI virtual tutor using a mixed-methods approach that combined a structured introduction session with semester-long usage monitoring and satisfaction assessment. In doing so, this chapter addresses both the practical design and implementation of the AI tutor and the empirical evaluation of its pedagogical effectiveness. These aspects were treated as inseparable, because the design choices embedded directly shaped the learning experience, and pedagogical evidence should, in turn, inform iterative refinement. We first present the theoretical foundations guiding AI-assisted learning, then describe our implementation approach, including the structured introduction strategy and longitudinal monitoring. We present quantitative usage data and student satisfaction results, followed by a discussion of pedagogical effectiveness, ethical considerations, and practical implications. Finally, these findings are synthesised into an evidence-based implementation framework intended to guide educators seeking to integrate AI virtual tutors into Physiology or Biochemistry courses. In addition, our findings contribute to the broader literature on AI in STEM education and offer practical insights for technology-enhanced learning in African higher education contexts. In these contexts, the need for scalable, personalised academic support is particularly pressing.

## 2. Theoretical Foundation

Teaching Molecular Physiology requires students to move fluidly between distinct scales, such as the behaviour of individual ion channels to the coordinated response of an organ system. In our experience of teaching BIC03B3, this is where many students struggle. A student may understand the biochemistry of a G-protein coupled receptor in isolation, but then struggle to understand how that propagates through a signal transduction cascade to produce a physiological outcome. The challenge is not a lack of effort, but rather a cognitive one. Cognitive load theory (Sweller, 1988; Sweller *et al.,* 2019) offers a useful lens for understanding why this is the case. Molecular Physiology imposes a high intrinsic cognitive load on students, because the content is irreducibly complex. Students are required to simultaneously hold multiple interacting elements in their working memory. This capacity is quickly saturated when a student tries to connect receptor activation, second messenger generation, kinase cascades, and downstream gene expression within a single conceptual frame. Traditional lectures compound the problem by adding extraneous load through fixed pacing determined by the lecturer, which cannot accommodate an individual student's point of confusion. An AI tutor addresses this directly by allowing students to isolate manageable aspects and request clarification at their own pace. Consequently, the tutor allows a reduction in extraneous load while preserving the intrinsic complexity of the content.

This capacity for adaptive, individualised support aligns closely with constructivist learning principles, which have long provided the pedagogical foundation for effective Science instruction (Driver *et al.*, 1994; Khare & Stewart, 2025; Grubaugh *et al.,* 2023). Constructivism holds that understanding is actively built rather than passively received, and that learners construct meaning most effectively when they can explore concepts at their own pace, connect new information to existing knowledge structures, and receive timely feedback (Driver *et al.,* 1994). In practice, this means that a student grappling with active transport across the plasma membrane benefits more from an interactive dialogue where they can ask follow-up questions, request analogies, and test their understanding, rather than from

re-reading a textbook passage. The AI tutor used in this study was configured with instructor-authored system instructions that deliberately embedded these constructivist scaffolding principles, as described in Section 3.2 (Richter *et al.,* 2024).

A related consideration is the role of self-regulated learning (SRL). Zimmerman's three-phase model: forethought, performance, and self-reflection, describes the metacognitive cycle through which effective learners plan, monitor, and adjust their study strategies (Zimmerman, 2002; Lan & Zhou, 2025). AI tutoring systems can support each of these phases. Regarding forethought, the chatbot helps students to identify gaps in their understanding by enabling targeted questioning. During performance, it provides real-time feedback as students work through concepts. It is arguable the most valuable is that students are afforded the opportunity of self-assessment where students direct the chatbot to create practice questions on topics of their choosing. This places learners firmly in the self-reflection phase, requiring them to evaluate what they know and what requires further study. As Lan and Zhou (2025) caution, AI tools that are too directive risk undermining the very metacognitive skills which they aim to develop. Therefore, our implementation followed a balanced approach by positioning the chatbot as a resource that students actively choose to consult, rather than a prescriptive system that dictates learning sequences.

Furthermore, these theoretical considerations intersect with Bloom's Taxonomy, particularly its application to digital learning environments (Churches, 2008). The chatbot interactions observed in this study span multiple cognitive levels. At the foundational level, concept clarification requests primarily engage the remembering and understanding tiers. However, when students use the chatbot to generate self-assessment questions and then evaluate their own responses, they move into the higher-order domains of analysis and evaluation. The capacity of AI tutors to operate across these cognitive levels distinguishes them from static learning resources, which typically address only lower-order recall.

Lastly, an important dimension that emerged as theoretically significant in our context is psychological safety.

Studies of help-seeking in STEM show that students often avoid asking questions when they fear judgement or appearing weak, which suppresses help-seeking behaviour (Flores *et al.*, 2022; Hsu *et al.*, 2025). This is of vital concern in a subject like Molecular Physiology, where terminology is dense and conceptual gaps compound rapidly; a single unasked question easily cascades into broader misunderstanding. AI tutors create an environment in which the perceived social cost of appearing uninformed is eliminated entirely. The non-judgemental nature of the interaction means that a student can ask the same question repeatedly, request progressively simpler explanations, or explore tangential curiosities without self-consciousness.

Empirical evidence increasingly supports these theoretical expectations. A meta-analysis of intelligent tutoring systems (ITS) encompassing 107 effect sizes and 14,321 participants found that ITS produced greater achievement than teacher-led large-group instruction ($g = 0.42$), non-ITS computer-based instruction ($g = 0.57$), and textbooks or workbooks ($g = 0.35$), with no significant difference between ITS and individualised human tutoring ($g = -0.11$) (Ma, 2014). Building on this established evidence base, a 2025 meta-analysis of 51 studies focusing specifically on generative AI tutoring reported a large positive effect size ($g = 0.867$) for AI tutoring on learning performance, with additional moderate effects on learning perception ($g = 0.456$) and higher-order thinking ($g = 0.457$) (Wang & Fan, 2025). Taken together, these meta-analyses demonstrate that AI tutoring represents a meaningful advance rather than a marginal supplement, and that well-designed systems can approach the effectiveness of individualised human tutoring.

Having established the theoretical foundations (cognitive load reduction, constructivist scaffolding, self-regulated learning support, and psychological safety) we now turn to their practical application. The methodology that follows describes how these principles were operationalised in the BIC03B3 Molecular Physiology module through the LearnBridge platform. Specifically, we detail the structured introduction strategy designed to establish usage patterns, the semester-long monitoring approach to capture authentic learning behaviours,

and the mixed-methods framework that would ultimately validate whether theoretical expectations translated into measurable educational outcomes.

# 3. Methodology

## 3.1. Study Design

This mixed-methods study employed a sequential explanatory design combining structured introduction activities, longitudinal usage monitoring, and satisfaction assessment. The research was conducted across a full academic semester in a Molecular Physiology course, following institutional ethical approval (2024-03-07/Koorsen) and informed consent procedures.

## 3.2. Implementation Framework

The AI tutor used in this study was deployed through LearnBridge, a custom-designed platform developed at the University of Johannesburg to coordinate AI-powered tutoring across multiple modules and faculties. LearnBridge provides the deployment, user management, and usage monitoring infrastructure, while the pedagogical configuration of each tutor resides in the underlying AI model. For the BIC03B3 module, the tutor was configured using OpenAI's Assistant API. The module learning guide, class notes, and supporting materials were uploaded as the tutor's knowledge base, and the system employed retrieval-augmented generation (RAG). Thus, for each student query, relevant passages from the uploaded course materials were retrieved and used to ground the tutor's response. This ensured that explanations remained aligned with the module curriculum and reduced the risk of inaccurate or off-topic content generated from the model's general training data. The instructor-authored system instructions also embedded constructivist scaffolding principles, directing the tutor to probe student understanding before offering explanations, to build from simpler to more complex representations, and to encourage students to articulate their reasoning. In this way, the pedagogical design resided in the instructional configuration crafted by the teaching team, while LearnBridge served as the deployment and monitoring framework. The tutor prompted to bear in mind that students were mostly first-generation university students and

non-native English-speakers. Since the BIC03B3 implementation reported here, LearnBridge has been adopted in additional modules across the University of Johannesburg, demonstrating the platform's scalability and adaptability to different disciplinary contexts.

The study implemented a three-phase approach designed to capture immediate perceptions and subsequent usage patterns to evaluate AI tutor adoption and educational effectiveness. Phase 1 consisted of an introduction and orientation through a single two-hour tutorial session implementing the "The AI Chatbot Challenge" to familiarise students with AI tutor capabilities, followed by immediate satisfaction assessment. The first hour focused on foundation and basic interaction, worth 20 marks, beginning with registration, login, and technical orientation during the initial 15 minutes. Students then engaged in Activities 1 and 2, covering concept clarification and simplification during minutes 15 to 45, followed by survey completion for these activities during minutes 45 to 60.

The second hour emphasised advanced features and assessment, also worth 20 marks. Students completed Activities 3 and 4, addressing multilingual learning and self-assessment creation during minutes 60 to 90, then engaged in Activity 5, involving comprehensive reflection and feedback during minutes 90 to 110. The session concluded with completion of a comprehensive 7-item satisfaction survey assessing student perceptions of the AI tutor experience, followed by a wrap-up and ongoing usage guidelines during the final 10 minutes.

The structured activities included five components designed to demonstrate different AI tutor capabilities. Activity 1 focused on clarifying concepts worth 5 marks, where students asked Biochemistry-related questions that they felt too shy or embarrassed to ask instructors or peers. Activity 2 involved explaining and simplifying concepts worth 5 marks, where students requested explanations of complex Molecular Biology concepts in simpler terms, including analogies. Activity 3 addressed using different languages, worth 5 marks, where students asked the chatbot to explain the "Fluid Mosaic Model" in their home language after reading a provided textbook passage.

Activity 4 concentrated on setting up a self-study assessment worth 5 marks, where students used the chatbot to create personalised self-assessment questions on chosen Biochemistry and/or Molecular Physiology topics. The AI system's large language model (LLM) generated these questions dynamically in response to student prompts, not from pre-programmed question banks. However, the LLM was limited in responses by the RAG that was system employed. Students could specify topics, difficulty levels, question formats, and other parameters, with the AI generating unique questions tailored to each request.

Activity 5 involved sharing thoughts worth 10 marks, where students completed comprehensive feedback on their experience.

Phase 2 encompassed autonomous usage and monitoring during weeks 2 to 16. Following the structured introduction and immediate satisfaction assessment, students used the chatbot autonomously while the lecturers monitored usage patterns, including temporal distribution, content themes, interaction purposes, and language preferences throughout the remainder of the semester. Phase 3 involved comprehensive data analysis, integrating the immediate post-introduction satisfaction data with semester-long usage patterns to evaluate the relationship between initial perceptions and sustained engagement behaviours.

### 3.3. Data Collection

Quantitative usage data included temporal usage patterns examining hourly and daily distributions, content theme classification across eight categories of Molecular Physiology topics, interaction purpose analysis covering four types of learning objectives, and language usage distribution. Quantitative satisfaction data employed a seven-item Likert scale survey ranging from one (Very Negative) to five (Very Positive), administered immediately following the Chatbot Challenge session. Items assessed understanding improvement, comfort asking sensitive questions, concept simplification helpfulness, likelihood of continued use for concepts and self-assessment, satisfaction with AI-generated content quality, and usefulness of self-assessment features. Qualitative feedback incorporated

open-ended responses during Activity 5 of the Chatbot Challenge and reflective comments on learning experiences and AI tutor effectiveness. For evaluation, only de-identified usage data were stored and analysed in aggregate.

### 3.4. Data Analysis

Quantitative data were analysed using descriptive statistics to characterise usage patterns and satisfaction scores. Temporal patterns were examined through frequency distributions across hours of day and days of week. Content themes and interaction purposes were analysed through categorical frequency analysis. Satisfaction scores were calculated as means with standard deviations and examined for distribution patterns. Mixed-methods integration followed established frameworks for triangulation, examining convergence between immediate post-introduction satisfaction perceptions and subsequent semester-long usage behaviour data to validate findings and provide a comprehensive understanding of AI tutor effectiveness. This approach enabled analysis of whether initial positive impressions translated into sustained engagement patterns and authentic learning integration.

## 4. Results

### 4.1. Usage Patterns Analysis

The chatbot usage demonstrated clear temporal patterns aligned with student study behaviours. Peak usage occurred during evening study hours, with the highest engagement between 18:00 and 19:00 (Figure 11.1). Secondary peaks appeared during afternoon study sessions (14:00-16:00) and consistent morning usage (10:00-12:00). Low usage periods occurred during early morning hours (2:00-6:00), providing optimal windows for system maintenance.

Weekly usage patterns revealed the highest engagement on Sundays (586 interactions), reflecting intensive examination preparation and study review activities (Figure 11.2). Steady weekday usage occurred Monday through Thursday (116-331 interactions), while Saturday showed significant weekend

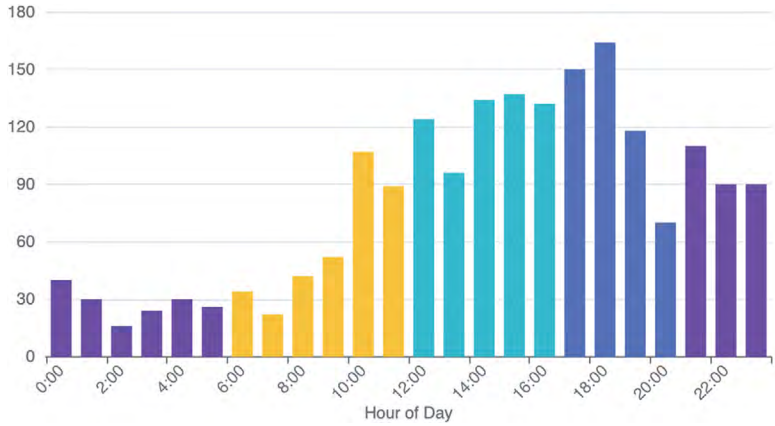



**Figure 11.1:** Temporal usage patterns of the chatbot by Hour of Day. Hourly distribution of the chatbot interactions throughout a typical day during the semester-long monitoring period. The data represents aggregated usage across all participating students. Colour-coding indicates different time periods: purple (0:00-6:00, early morning), yellow (7:00-11:00, morning), cyan (12:00-17:00, afternoon), blue (18:00-21:00, evening), and purple (22:00-23:00, late evening).

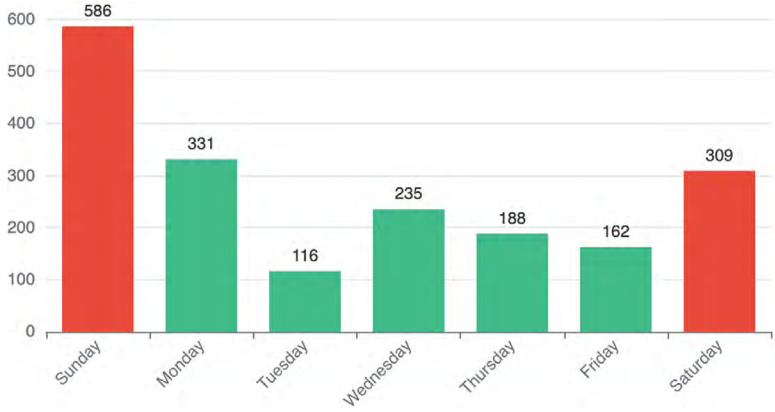



**Figure 11.2:** Weekly usage distribution of chatbot interactions: distribution of the chatbot usage across days of the week during the semester monitoring period. Sunday showed the highest engagement (586 interactions), reflecting intensive examination preparation and study review activities. Red bars indicate weekend days; green bars represent weekdays.

study activity (309 interactions). Tuesday demonstrated the lowest weekday usage (116 interactions), suggesting mid-week scheduling conflicts with other academic activities.

Student interactions concentrated on core Molecular Physiology concepts, with signal transduction pathways receiving the highest engagement (68 interactions, 9.7% of categorised content) (Figure 11.3). Plasma membrane structure and function followed closely (66 interactions, 9.39%), reflecting the fundamental importance of these topics in Molecular Physiology education. Immune system components and functions generated substantial interest (47 interactions, 6.69%), while specialised topics including muscle physiology and metabolism, haemostasis and thrombosis, active and secondary transport mechanisms, and HIV immunology each received focused attention (28-31 interactions each). The substantial "Other" category (404 interactions, 57.47%) indicates diverse student interests beyond the predefined categories, suggesting broad utility across the Molecular Physiology curriculum.

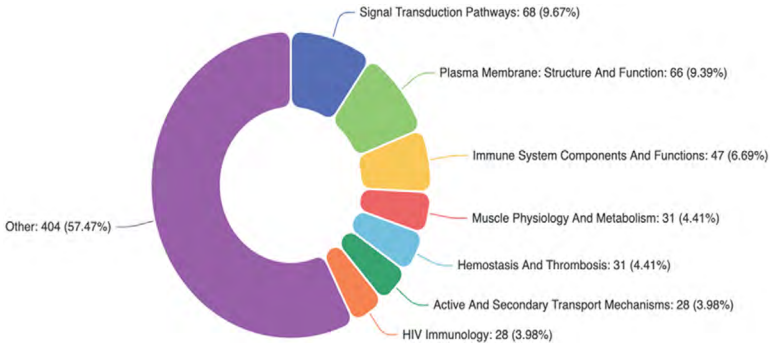



**Figure 11.3:** Content theme distribution in the chatbot interactions. Pie chart showing the distribution of student interactions across Molecular Physiology content themes during semester-long monitoring. Signal transduction pathways received the highest engagement (68 interactions, 9.67%), followed by plasma membrane structure and function (66 interactions, 9.39).

Concept clarification dominated student interactions with the chatbot, comprising 84.9% of all categorised purposes (416 interactions) (Figure 11.4). This finding validates the primary educational value of AI tutors in providing accessible explanations of complex Molecular Physiology concepts. Self-assessment and assessment-related activities constituted 6.33% of interactions (31 interactions), while study tips and strategies accounted for 5.71% (28 interactions). The minimal "Other" category (15 interactions, 3.1%) suggests that the identified purposes comprehensively captured student usage patterns.

English overwhelmingly dominated language usage at 98.7% of interactions, with other languages comprising only 1.3% (Figure 11.5). This distribution reflects the English-medium instruction context while demonstrating some utilisation of multilingual capabilities, particularly relevant for diverse student populations in higher education settings.

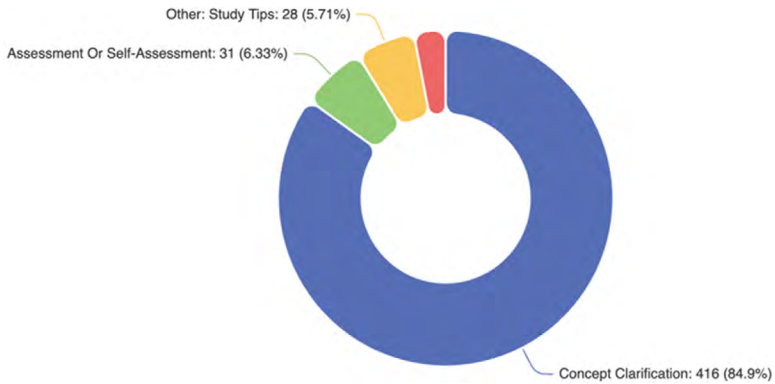



**Figure 11.4:** Purpose classification of the chatbot interactions. Pie chart illustrating the distribution of interaction purposes during semester-long chatbot usage. Concept clarification dominated student interactions, comprising 84.9% of all categorised purposes (416 interactions), validating the primary educational value of AI tutors in providing accessible explanations of complex Molecular Physiology concepts.

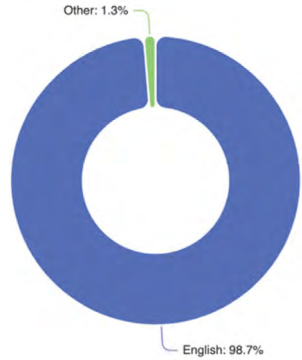



**Figure 11.5:** Language usage distribution in the chatbot interactions. Pie chart showing language preferences in the chatbot interactions throughout the semester monitoring period.

## 4.2. Student Satisfaction Analysis

Student satisfaction with the chatbot, measured immediately following the introduction session, demonstrated very positive results across all measured dimensions, with scores ranging from 4.36 to 4.76 on a five-point scale (Figure 11.6). Self-assessment generation achieved the highest satisfaction score (4.76/5.0), indicating that students immediately recognised the superior value of AI performance in creating educational assessments and practice materials based on their brief experience during the introduction session. This finding proved prescient, as subsequent usage data showed sustained engagement with self-assessment features (Table 11.1) throughout the semester, validating students' initial positive impressions.

**Table 11.1:** Self-Assessment conversation formats and example prompts used by students

| Conversation Format | No.* | Example Student Prompt |
|---|---|---|
| Multiple-choice questions (MCQ) | 21 | "Give me difficult MCQ on apoptosis" |
| Application-based questions | 9 | "Provide application questions" |

(*Continued*)

**Table 11.1:** Self-Assessment conversation formats and example prompts used by students(*Continued*)

| Conversation Format | No.* | Example Student Prompt |
|---|---|---|
| Short answer questions | 5 | "What short answer questions can be asked on cell membrane transport" |
| True/False questions | 1 | "Create true or false questions about the fluid mosaic model" |
| Fill-in-the-blank questions | 3 | "Create a fill in the missing words self assessment on membrane transport protein" |
| Difficulty-levelled questions | 2 | "Set up questions and answers on glycolysis on different difficulty levels" |
| Model answers requested | 11 | "Provide correct model answers to this assessment" |
| Exam-style question generation | 3 | "How would you ask this in an exam question?" |

** The number of self-assessment prompts used by students.*

Psychological safety in asking sensitive questions received the second-highest satisfaction rating (4.71/5.0), confirming a critical advantage of AI tutoring systems. Students felt highly comfortable asking questions that they might hesitate to ask human instructors or peers, addressing traditional barriers to help-seeking in challenging Science courses. This psychological safety benefit proves particularly valuable in Molecular Physiology education, where complex concepts often generate student uncertainty and misconceptions.

Likelihood of continued use for concept simplification also achieved high satisfaction (4.71/5.0), indicating genuine perceived value beyond initial novelty effects. This finding suggests sustainable engagement with AI tutoring systems and validates

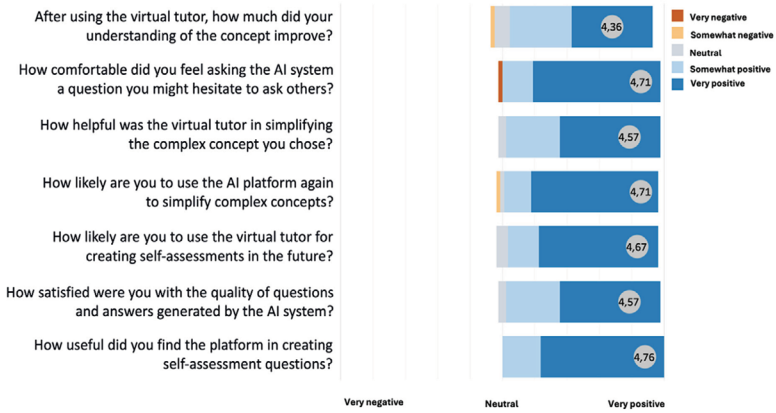



**Figure 11.6:** Student satisfaction survey results following the chatbot introduction session. The horizontal bar chart displays student satisfaction scores across seven dimensions measured immediately following the two-hour Chat Challenge introduction session. All scores ranged from 4.36 to 4.76 on a five-point Likert scale (1=Very Negative, 5=Very Positive). Colour-coding progresses from lighter to darker blue, indicating increasing satisfaction levels. The consistently high scores demonstrate exceptional student acceptance and predicted educational value that was subsequently validated by semester-long usage patterns.

long-term implementation viability. Similarly, the likelihood of continued use for self-assessment creation showed strong positive responses (4.67/5.0), supporting the integration of AI tutors into ongoing study routines.

Concept simplification effectiveness received high satisfaction ratings (4.57/5.0), validating AI tutors' ability to translate complex Molecular Physiology terminology into accessible explanations. The quality of AI-generated questions and answers achieved equally strong satisfaction (4.57/5.0), confirming the pedagogical appropriateness of AI-produced content for Molecular Physiology education. Understanding improvement showed the lowest but still highly positive satisfaction score (4.36/5.0) based on students' immediate post-introduction assessment, with 87% of students reporting

anticipated improved conceptual understanding after using the chatbot. This finding provides evidence of initial learning effectiveness perception and supports the educational value proposition of AI tutoring systems, later validated by sustained semester-long usage patterns focused on concept clarification.

### 4.3. Mixed-Methods Integration

The convergence between immediate post-introduction satisfaction perceptions and subsequent semester-long usage behaviour provides strong validation of the chatbot's effectiveness and students' ability to accurately assess AI tutor value from initial exposure. High immediate satisfaction with concept clarification (4.57/5.0) proved predictive of usage patterns, showing that 84.9% of interactions focused on this purpose throughout the semester. The strong initial satisfaction with self-assessment generation (4.76/5.0) corresponded directly to sustained engagement with these features across the full academic term.

The students' immediate predictions about psychological safety and continued usage proved remarkably accurate. The high initial satisfaction scores for comfort in asking sensitive questions and likelihood of continued use were validated by consistent engagement across study periods and diverse content themes throughout the semester. This convergence suggests that students can accurately evaluate AI tutor benefits from intensive introduction experiences. Few negative responses in any satisfaction category after introduction, combined with steady usage all semester, suggest that students found genuine value in the features rather than being temporarily impressed by the technology. The consistency between immediate satisfaction and long-term usage behaviour strengthens confidence in both the AI tutor's effectiveness and the validity of using intensive introduction sessions to predict sustained adoption.

## 5. Discussion

### 5.1. Educational Effectiveness

The implementation of this chatbot provides compelling evidence for AI virtual tutor effectiveness in Molecular Physiology education. The very high satisfaction scores (4.36-4.76/5.0)

measured immediately after the introduction session, combined with sustained usage patterns throughout the semester, focused on concept clarification, representing 84.9% of interactions, validate both students' ability to accurately assess AI tutor value from initial exposure and the genuine educational effectiveness of well-designed AI tutoring systems. Eighty-seven per cent of students who predicted improved understanding based on their introduction experience turned out to be correct, as demonstrated by steady engagement throughout the academic term.

The dominance of concept clarification in subsequent usage patterns (84.9% of interactions) confirms that students accurately predicted AI tutors' primary educational function during their initial experience, making complex Molecular Physiology concepts accessible. This predictive accuracy supports both the validity of intensive introduction sessions and constructivist learning theory applications, where AI systems provide the scaffolded, adaptive support necessary for active knowledge construction (Khare & Stewart, 2025). The convergence between immediate satisfaction assessments and sustained usage behaviour strengthens confidence in these conclusions.

## 5.2. Psychological Safety and Help-Seeking

High initial psychological safety (4.71/5.0) was a key factor in breaking down typical barriers to students seeking help in Science education. This positive impact was then reinforced by their sustained engagement with various content themes throughout the semester. Students' immediate comfort in asking questions that they might hesitate to ask others, as measured directly after the introduction session, proved predictive of long-term usage patterns, validating research showing that fear of negative evaluation suppresses help-seeking in STEM contexts (Flores *et al.*, 2022; Hsu *et al.*, 2025). This psychological safety proves particularly valuable in Molecular Physiology education, where abstract concepts and complex terminology often generate student uncertainty. The sustained engagement across diverse content themes demonstrates that psychological safety benefits extend beyond specific topics to general learning confidence. This finding suggests that AI tutors may help to develop broader

help-seeking behaviours that transfer to other educational contexts, though longitudinal research is needed to confirm this potential benefit.

### 5.3. Self-Assessment Excellence

The highest immediate satisfaction score for self-assessment generation (4.76/5.0) revealed an unexpected strength of AI tutoring systems that students recognised during their first exposure. Students found great value in AI-generated practice questions, model answers, and explanations based on their introduction session experience, suggesting that AI tutors may excel beyond concept clarification to include assessment creation. This capability addresses a significant challenge in Molecular Physiology education, where creating diverse, appropriately challenging practice materials requires substantial instructor time and expertise. The subsequent semester-long usage patterns confirmed students' initial assessment, with sustained engagement in self-assessment activities validating their immediate positive impressions. The combination of high satisfaction with self-assessment generation and sustained usage patterns indicates that AI tutors successfully support self-regulated learning processes. Students appear to value the autonomy and flexibility of creating personalised assessment materials while benefiting from immediate feedback and explanation capabilities.

### 5.4. Temporal Optimisation

The clear temporal usage patterns provide practical guidance for AI tutor implementation. Peak evening usage (18:00-19:00) and weekend study periods align with traditional study behaviours while demonstrating that AI tutors effectively fill gaps when human support is unavailable. The consistent weekday engagement suggests integration into regular study routines rather than episodic usage. These findings support the value proposition of 24/7 AI tutor availability while informing resource allocation and system maintenance scheduling. The alignment between usage patterns and typical study behaviours validates the ecological validity of AI tutor implementation in authentic educational contexts.

## 5.5. Implementation Framework Validation

The success of the single two-hour Chatbot Challenge in generating both high immediate satisfaction and establishing sustained usage patterns validates an efficient implementation approach that maximises predictive accuracy. The structured introduction combining hands-on experience with immediate satisfaction assessment proved enough not only to demonstrate AI tutor capabilities but also to enable accurate student evaluation of long-term educational value. This finding has significant practical implications for institutions considering AI tutor implementation, suggesting that intensive short-term introduction sessions can serve dual purposes: providing comprehensive exposure and generating reliable predictive data for sustained adoption success. The assessment-integrated approach (40 marks total) likely contributed to serious student engagement while providing comprehensive exposure to AI tutor capabilities. Progression from basic concept clarification through advanced self-assessment creation offers a replicable model for other Molecular Physiology or Science education contexts.

(a) **Language Use and the Multilingual Context**

The near-exclusive use of English in chatbot interactions (98.7%) warrants careful interpretation, particularly given that the BIC03B3 cohort at the University of Johannesburg is linguistically diverse, with the majority of students speaking an African language as their home language. Despite the chatbot's multilingual capability, demonstrated during the introduction session when students were explicitly asked to request explanations in their home languages, usage reverted almost entirely to English.

While investigating the causes for this surprising result was beyond the scope of this study, several factors likely contribute to this pattern. Molecular Physiology terminology is overwhelmingly English-derived, and many core concepts lack established equivalents in South African languages. A student seeking clarification on "signal transduction" or "G-protein coupled receptors" would find that switching languages introduces an additional translation burden rather than reducing cognitive load. Moreover, students in the South African higher education system

are assessed exclusively in English, which creates a pragmatic incentive to study and practise in the language of examination.

This finding does not diminish the potential value of multilingual AI tutoring. Rather, it suggests that simply making a multilingual option available is insufficient. Students may need explicit encouragement and structured activities that frame home-language engagement as a legitimate cognitive strategy rather than a departure from "proper" academic practice. This represents an important area for further research, particularly in multilingual African higher education contexts where the tension between home-language cognition and English-medium instruction remains a challenge.

(b) **Ethical, Accessibility, and Data Privacy Considerations**

In higher education, AI virtual tutors raise critical ethical and practical concerns. Student data privacy is of particular concern, as these systems collect sensitive information, necessitating robust data protection and informed consent (Marín *et al.*, 2025; García-López & Trujillo-Liñán, 2025). Another consideration is algorithmic, because AI tutors trained on biased data can unintentionally reinforce inequities in learning outcomes (Al-Zahrani, 2024; Cotilla Conceição & van der Stappen, 2025). Moreover, while AI tutors can personalise learning, a lack of inclusive design or unequal access to technology may further disadvantage some student groups (Cotilla Conceição & van der Stappen, 2025; Al-Zahrani, 2024). The digital readiness of students and educators is equally important; without sufficient digital literacy and training, AI tutor integration may falter and widen the digital divide (Al-Zahrani, 2024; Marín *et al.*, 2025), Ethical guidelines, bias mitigation, and capacity-building is, therefore, important to responsibly harness AI's educational benefits.

In our implementation, evaluation data were stored only in de-identified form and mostly analysed at an aggregate level (e.g., temporal patterns, broad topic categories, language, and interaction purposes). To reduce off-curriculum or misleading responses, the tutor was grounded in module materials, and the introduction session oriented students to treat the AI as supportive rather than authoritative.

(c) **Limitations and Future Research**

Several limitations should be considered with these findings. Because the study was conducted in only one Molecular Physiology module at one institution, the results may not generalise to different educational contexts, student populations, or AI tutoring systems. The semester-long timeframe, while substantial, does not address long-term retention effects or impact on academic trajectory outcomes. The predominantly English language usage (98.7%) reflects the instructional context but limits conclusions about multilingual AI tutor effectiveness. Future research should examine AI tutor performance across diverse linguistic contexts and explore potential benefits for English language learners in science education.

The high satisfaction scores, while encouraging, require validation through objective learning outcome measures, including pre/post assessments, knowledge retention testing, and comparison with control groups receiving traditional instruction. Additionally, the relationship between AI tutor usage and module performance warrants investigation to establish causal connections between AI tutor engagement and academic achievement. Longitudinal studies examining sustained learning impacts over multiple semesters or years would strengthen the understanding of the educational value of AI tutors. Research addressing transfer effects to related courses and professional applications would inform broader implementation decisions.

## 6. Practical Implications

These chatbot findings offer several practical implications for Molecular Physiology educators and educational technology administrators. The demonstrated effectiveness of a single intensive introduction session provides a scalable model for AI tutor implementation that minimises disruption to existing curricula while maximising student exposure and engagement. The concentration of usage on concept clarification suggests that AI tutors should be positioned as supplementary support systems rather than primary instruction replacements. This positioning aligns with constructivist pedagogical principles while addressing practical concerns about AI tutors displacing human instruction.

The exceptional performance in self-assessment generation indicates that AI tutors may be particularly valuable for supporting independent study and exam preparation activities. Educational institutions might consider integrating AI tutors specifically into study skills programmes and academic support services. The temporal usage patterns suggest that AI tutor effectiveness depends on seamless integration into existing study behaviours rather than requiring behaviour change. Implementation strategies should emphasise convenience, accessibility, and alignment with student preferences rather than prescriptive usage requirements.

The theoretical foundations, empirical findings, and practical insights presented thus far converge in the comprehensive implementation framework that follows. This framework synthesises constructivist pedagogical principles with usage pattern evidence and satisfaction data to provide actionable guidance for educators. By integrating the validated three-phase introduction model, the demonstrated temporal and content usage patterns, and the quality assurance measures necessary for sustained effectiveness, the framework operationalises the research findings into a replicable roadmap.

## 7. Evidence-based Implementation Framework

Based on the chatbot research findings, we propose an evidence-based framework for implementing AI-powered virtual tutors in Molecular Physiology education (Figure 11.7). This framework integrates theoretical foundations with empirical validation to provide practical guidance for educational institutions. The framework operates through three sequential phases designed to maximise adoption and educational effectiveness. The first phase involves a structured introduction through a single two-hour session validated by the Chatbot Challenge model with progressive skills development (Figure 11.7). This phase begins with technical orientation covering registration, login, and basic navigation during the initial 15 minutes. Students then engage in concept clarification practice involving guided experience, asking sensitive or complex questions for 30 minutes, followed by simplification exercises requesting explanations using analogies and accessible

language for another 30 minutes. Multilingual exploration allows students to experience explanation in preferred languages for 15 minutes, while self-assessment creation enables the generation of practice questions with varying difficulty levels for 30 minutes. The session concludes with reflection and planning involving completion of the satisfaction assessment and planning for ongoing usage during the final 20 minutes. Assessment integration through a 40-mark structure ensures serious engagement while providing comprehensive evaluation data.

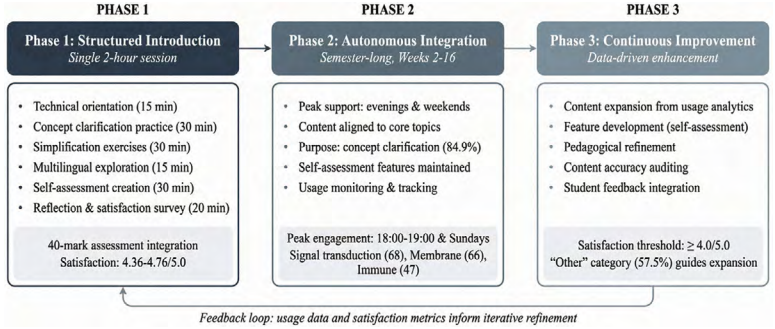



**Figure 11.7:** Evidence-based implementation framework for AI virtual tutors in Molecular Physiology education. The three-phase model is grounded in empirical findings from the BIC03B3 chatbot implementation. Phase 1 details the validated Chatbot Challenge introduction session structure. Phase 2 outlines semester-long autonomous integration priorities derived from observed usage patterns. Phase 3 describes data-driven continuous improvement informed by usage analytics and satisfaction metrics. Grey highlighted text beneath each phase indicates the specific empirical evidence base. The feedback loop represents iterative refinement driven by ongoing usage data and satisfaction monitoring.

The second phase encompasses autonomous integration throughout the semester, with usage optimisation supporting natural adoption patterns based on empirical findings (Figure 11.7). Peak support hours ensure optimal system performance during 18:00-19:00 and weekend periods when student engagement is highest. Content alignment focuses AI tutor training on core Molecular Physiology topics, including signal transduction,

membrane function, and immune systems, based on usage analysis. Purpose prioritisation emphasises concept clarification capabilities, representing 84.9% of usage while maintaining self-assessment features that received the highest satisfaction scores. The monitoring framework tracks key indicators of successful implementation, including sustained engagement across the academic semester, distribution of usage across content themes and learning purposes, student satisfaction maintenance above the 4.0/5.0 threshold established by the chatbot findings, and integration into regular study behaviours rather than occasional usage.

The third phase focuses on continuous improvement through data-driven enhancement using usage analytics and satisfaction feedback for ongoing optimisation (Figure 11.7). Content expansion based on analysis of the substantial "Other" category in usage patterns allows institutions to respond to diverse student interests. Feature development prioritises high-satisfaction capabilities such as self-assessment generation while technical improvements are informed by usage pattern analysis. Pedagogical refinements based on learning outcome assessment ensure continued educational effectiveness. Quality assurance maintains educational effectiveness through regular content accuracy auditing by subject matter experts, pedagogical appropriateness review of AI-generated materials, student feedback integration for continuous improvement, and performance monitoring against learning objective alignment.

Institutional requirements include technical infrastructure providing reliable Internet connectivity supporting peak usage periods, scalable server capacity accommodating concurrent users, data security protocols protecting student interaction privacy, and integration capabilities with existing learning management systems. Faculty development encompasses training in AI tutor capabilities and limitations, pedagogical integration strategies for different learning objectives, assessment design incorporating AI tutor components, and ongoing support for technology adoption and optimisation.

Student support includes clear guidelines for effective AI tutor utilisation, academic integrity policies addressing

AI assistance boundaries, technical support for access and usage difficulties, and resources for maximising learning benefits based on the chatbot experience.

Success metrics incorporate both quantitative and qualitative indicators. Quantitative indicators include student satisfaction scores at or above 4.0/5.0 across all dimensions, usage frequency indicating regular integration into study routines, content engagement aligning with course learning objectives, and learning outcome improvements compared to baseline performance. Qualitative indicators encompass student reports of improved confidence in asking questions, enhanced engagement with challenging Molecular Physiology concepts, increased autonomy in self-directed learning activities, and positive integration into collaborative learning environments. Institutional indicators measure faculty satisfaction with AI tutor impact on teaching effectiveness, reduced demand for traditional tutoring services, improved course evaluation scores related to learning support, and successful scaling across multiple courses or programmes.

## 8. Conclusion

The chatbot implementation provides robust empirical evidence supporting the effectiveness of AI-powered virtual tutors in Molecular Physiology education, aligning with meta-analytic evidence demonstrating positive effects on learning performance, perception, and higher-order thinking (Wang & Fan, 2025). Exceptional student satisfaction scores ranging from 4.36 to 4.76 on a five-point scale, sustained usage patterns focused on concept clarification representing 84.9% of interactions, and successful integration into study behaviours validate the educational value of well-designed AI tutoring systems. The research demonstrates that AI virtual tutors excel in three critical areas that directly address key challenges in Molecular Physiology education. First, they create psychologically safe learning environments where students feel comfortable asking sensitive questions, achieving a satisfaction score of 4.71/5.0 that represents a breakthrough in addressing traditional help-seeking barriers. Second, they provide effective concept simplification for

complex Molecular Physiology topics with a satisfaction score of 4.57/5.0, supporting constructivist learning principles through scaffolded, adaptive support. Third, they generate high-quality self-assessment materials with the highest satisfaction score of 4.76/5.0, addressing the significant challenge of creating diverse, appropriately challenging practice materials in Molecular Physiology education.

The validated implementation framework offers practical guidance for educational institutions by demonstrating that a single intensive introduction session can establish sustained AI tutor adoption while maximising educational benefits. The time-based usage patterns show peak engagement during evening hours and weekend periods, content preferences concentrating on core Molecular Physiology topics, and interaction purposes dominated by concept clarification provide evidence-based insights for optimising AI tutor deployment and resource allocation. While there are limitations around how broadly these results apply to other educational contexts and measuring long-term impact, the chatbot findings make an important contribution to understanding AI tutor effectiveness in higher education Science. The convergence of theoretical foundations rooted in constructivist and social learning theories, empirical validation through mixed-methods research, and practical implementation guidance creates a foundation for the broader adoption of AI-powered virtual tutors in Molecular Physiology and related scientific disciplines.

The exceptional effectiveness demonstrated by the chatbot, particularly in creating psychological safety for help-seeking behaviours and generating high-quality self-assessment materials, suggests substantial potential for transforming Molecular Physiology education through thoughtful integration of artificial intelligence technologies. Future research should extend these findings through longitudinal studies examining retention and transfer effects, controlled comparison trials establishing causal relationships between AI tutor usage and learning outcomes, and cross-institutional validation to strengthen the evidence base for AI tutoring in science education.

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Chapter 12

# An exploration of generative AI-resistant computational thinking: Remote assessment strategies

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## Abstract

The rise of generative artificial intelligence systems capable of performing basic programming tasks has negatively impacted the ability of such competencies to be assessed remotely. While this may lead to a return to in-person assessment for such competencies, as is the case in other numerical sciences, there are still use-cases where remote assessment is preferable, such as in the case of screening applicants to large courses. While the situation can be dealt with as a generalisation of the pre-existing problem of establishing genuine authorship via online proctoring tools, such methods have severe implementation constraints in terms of user acceptance, technical issues, and privacy concerns. Consequently, the need exists to explore other possible assessment strategies that make use of the asymmetric imbalance in performance across differing assessment modalities inherent in the current generation of generative artificial intelligence (AI). This work explores such strategies and formalises these approaches into a generalised process for online assessment.

The work poses two related families of research questions firstly considering what learning styles current AI approaches excel at and secondly what shortcomings in those learning styles can be exploited to ensure that authentic assessment takes place. The resulting metaheuristic for assessment design is referred to as AI-resistant computational thinking and can be employed across various educational domains beyond Computer Science and STEM to construct authentic assessment opportunities in an age of advancing AI capabilities. The discussion is framed through the experience of transitioning an introductory programming service module within the Academy of Computer Science and Software Engineering to automated assessment, along with the curriculation of foundational modules for an extended degree.

**Keywords:** Assessment Strategies, Computational Thinking, Generative AI.

## 1. Introduction

The 2020s have seen the convergence of a set of independent global factors that continue to have a dramatic impact on the successful delivery of the academic project across both first-world and developing nations. The global coronavirus disease 2019 (COVID-19) pandemic and related extended shelter-in-place / lockdown orders coincided with the tail end of a period of rapid expansion of access to digital communication, mobile, and Web-based technologies during the first quarter of the 21st century (Zhao & Semachew, 2025). It is worth mentioning that while this expansion has been widespread and pervasive it has by no means been universal with many communities such as those in rural South Africa still being marginalised in terms of their access to, and ability to participate in, the global knowledge economy (Mwansa *et al.*, 2025). This combination resulted in a large-scale natural experiment regarding the resilience of academic offerings in general to remote assessments. The results of subsequent studies of the impact of remote assessments and related techno-stressors have shown several negative consequences in both international (Zhang *et al.*, 2022) and South African (Mangunda, 2024) settings. Current research has emphasised the

need for Pan-African responses to the potential impact of AI on higher education (Guadu *et al.*, 2026).

A further confluence of factors was seen, namely the apparently serendipitous development of the transformer neural network architecture (Vaswani *et al.*, 2017) and subsequent development of pretrained large language model (LLM) based generative AI (Radford *et al.*, 2018) coinciding with the emergence of widespread techno-stressors relating to the explosion of complexity faced by students in the modern digital era. These developments initially seemed to provide the tools necessary to deal with the increased cognitive load arising from an overwhelming availability of information sources in much the same way that PageRank-based search engines such as Google provided in previous decades (Brin & Page, 1998).

However, the difference in terms of cognitive capacity impact between a search engine that provides links to content and a generative artificial intelligence system that actively answers questions is not insignificant. Recent studies, including a major work from MIT (Kosmyna *et al.*, 2025) show that the impact of over-reliance on LLMs impacts the cognitive development of students within the context of essay-based assessment. Additionally, these systems, being based on transformers which have been pretrained on large corpora of preexisting work, raise issues relating to the establishment of genuine authorship for student work. LLMs and other generative AI are being increasingly integrated into the world of work, which students must enter, so it is also not possible to simply ignore their existence.

Consequently, the balance between the negative impacts of generative AI being the antithesis of the needs of the academic project and its undeniable role in the world means that the topic is worthy of further consideration within the context of the scholarship of teaching and learning. It is also worth noting that while the MIT results focused on essay-based tasks, LLMs have seen widespread use in software development, and, therefore, the literature needs to be explored to ascertain if the results for essay-based assessment hold true for software development tasks. It is important to note that the risks posed by AI are not merely

those of academic integrity in the form of cheating or plagiarism but a deeper issue of academic authenticity in terms of the degree to which the assessment reflects the actual learning imparted.

Therefore, there is a real need for strategies to allow for the following research questions to be addressed:

- RQ1: Are monitoring and detection viable strategies for remote assessment in the age of generative AI?
- RQ2: Is there evidence to suggest that cognitive impairment occurs in software development tasks as a result of over-reliance on generative AI?

The following research questions are based on the following assumption, which will be substantiated via literature review: Current LLM-based AI systems are not general intelligences. It then follows that because the only known general intelligence (human beings) shows uneven competence across a variety of cognitive tasks that similar biases towards certain kinds of tasks should exist in such AI systems.

- RQ3: What is the learning style of modern generative AI?
- RQ4: Are there tasks that measure the required aptitudes for software development that humans perform well or that current generative AI do not handle well?
- RQ5: How sensitive is LLM performance to the provided prompt in software engineering tasks?
- RQ6: What strategies can be derived from the answers to the previous research questions to facilitate online assessment?

It is worth noting that these questions impact more than just assessment design from the point of view presenting academic modules. These questions impact the authenticity of self-reflective essays which are so important to the scholarship of teaching and learning. For the purposes of this work, the term "computational thinking" refers to those problem-solving abilities required to solve programming and software development-related problems. However, it should be noted that ability to think in terms of the stepwise refinement of processes, abstraction and specification, iteration and recursion, and in terms of nested structures applies to a much broader range of fields than Computer Science.

### 1.1. Context

These questions are considered from the viewpoint of the remote assessment needs of the Academy of Computer Science and Software Engineering, which is a department in the Faculty of Science at the University of Johannesburg. The academy offers a variety of qualifications at National Qualification Framework (NQF) levels 5 through 10. Within those qualifications, there are specific modules for which remote (or at least automated) assessment is important. These modules range from AI-specific short learning programmes, foundational computational intelligence extended modules, mainstream first-year Computer Science and Software Engineering modules, to a second-year service module for teaching introductory programming to second-year Accountancy students.

While the overall trend has been to move towards observable assessment (such as in-person exams and oral defences of project work) for summative assessment opportunities, there is still a great need for remote automated assessment for formative assessment opportunities. The typical pattern within the academy is for weekly formative practical programming assignments to be issued for completion at the students' own pace, with in-person assessment and feedback provided by student assistants the following week after submission. Such an approach necessitates the availability of a large pool of competent student assistants, which is not always possible for both financial and availability of competence-related reasons. There has been suggestion that within the context of online assessment in the age of AI the adoption of ethical frameworks based around transparency, accountability and human agency may be especially well-suited to African university assessment practice (Guadu *et al.*, 2026). Similarly, global bodies such as UNESCO advocate for a balance between the risks and opportunities for AI in education and research (Miao & Holmes, 2023)

## 2. Literature Review

In order to address the research questions posed previously, it will be necessary to first establish how software development-based modules are often assessed remotely. Following that, the impact

of generative AI on software development tasks and its impact on skill acquisition will be considered. The fundamental architecture of LLM-based systems will be reviewed with an emphasis on the degree to which they meet the criteria of artificial general intelligence. The multi-faceted nature of intelligence will be explored and mapped onto the much more limited pattern mining-based intelligence evident in LLMs. It is also beneficial to distinguish between the concepts of AI-assisted, AI-enhanced, and AI-resistant assessments. AI-assisted assessments are identical to conventional assessments but accelerated in terms of the deployment or evaluation by way of AI tooling. AI-enhanced assessments rely on some key features of modern AI to deliver an assessment opportunity that would not be possible without them. Finally, AI-resistant assessments exploit weaknesses within AI reasoning to create assessments which authentically reflect human learning while stymieing AI attempts to complete them.

It is also worth considering that while this research is predicated on the positive assumption that the development of AI-resistant assessment strategies is both meaningful and achievable recent research suggests that assessment in the context of AI has the characteristics of a "wicked problem" and may not be amenable to such solutions (Corbin et. al., 2025).

## 2.1. Online Assessment of Practical Programming Abilities

Automatic Assessment Tools (AATs) for the online assessment of programming assignments have existed long before the COVID-19 pandemic necessitated their rapid uptake and adoption in a more general sense. The 2010s saw the emergence of massive online open courses (MOOCs) (King & Lee, 2022). Their emphasis on large international cohorts with low barriers to entry and an emphasis on self-paced learning with asynchronous assessment made the usage of learning management systems (LMSs) coupled with AATs a necessity, as manual assessment methods would not scale to such large cohort sizes in terms of either cost, turnaround time, or consistency.

A recent systematic review of the literature (Messer *et al.,* 2024) of AATs was conducted, covering 121 such systems in

terms of their ability to assess the correctness, maintainability, readability, and documentation of programming assignment submissions. In general, the study found that two overall approaches to assessing quality were adopted, firstly in the form of static analysis (analysis without running the program) of the source code and other textual submissions. And secondly, via dynamic evaluation of the compiled executable versions of those submissions against a series of test cases (that is running the programs and comparing their output with expected values for the inputs that they were given). The second case is far easier to implement and, therefore, makes up the bulk of feedback provided by such systems. Reliance on black box-style dynamic evaluation has severe drawbacks in terms of only being able to inform students on which test cases they failed to correctly pass, but not necessarily on why their programs produce the output that they do.

Historically, any static analysis would need to be conducted by either making use of compiler construction techniques, such as converting the programs into an abstract syntax tree (AST) or other graph-based representations and then calculating software quality metrics based on those structures (such as cyclomatic complexity scores based on the flow of control through the program). Additionally, it is possible to then compare the student's solution to some reference solution by way of either calculating the graph distance between their respective AST or the edit distance between their source code directly. Neither of these is ideal, as it presupposes the uniqueness of the reference solution and would unfairly penalise students who had produced work that solved the problem in a different manner. It is, therefore, clear that more nuanced approaches are needed and recent work has been investing in the application of generative AI to the provision of student feedback for programming assignments (Gambo *et al.*, 2024).

## 2.2. Ensuring Honest Assessment for Remote Programming Assignments

Historically, within the Academy, the primary source of academic dishonesty in the weekly programming practical assignments

would be students directly copying from each other or attempting to pass off an assessment from a previous year as one for the current year. As the specific details of each assessment vary from year to year, the students would need to spend some measure of effort in adjusting any previous answers to match the problem domain of the current year's version. While such effort is undeniably less than writing an entirely original solution, in practice, many students would submit the previous memoranda completely unaltered, allowing detection by the student assistants grading the assignment. Furthermore, the feedback portion of the assessment allowed the student assistant to identify any suspicious patterns within their assigned marking groups. This is a sub-optimal arrangement at best, as code-sharing groups may be spread across multiple marking assistants, making identification difficult and, secondly, not all marking assistants are equally adept at identifying such patterns.

Consequently, automatic copy detection tools for programming assignments have been developed over the years. The code copy detection problem shares many similarities with that of assigning a mark based on static structure comparison with a reference solution discussed earlier. As with automatic evaluation, there are, broadly speaking, two ways to approach the problem, depending on the level at which the source code artefacts are compared. Firstly, the comparison can be made at the lexical level in a manner very similar to those used by conventional plagiarism detection tools such as Turnitin (the de facto standard tool in use at the University of Johannesburg) (Meuschke, 2023) or via a comparison of their grammatical structure as captured in their ASTs. There are differences between these approaches in terms of their operation as well as their advantages and disadvantages. The latter approach is rooted in compiler construction, while the former is rooted in unstructured text analysis. While the lexical analysis techniques may seem simpler than those based on actually parsing the source code into a tree representation, it is worth considering them second, as they lie on a spectrum of techniques culminating in those used in modern generative AI.

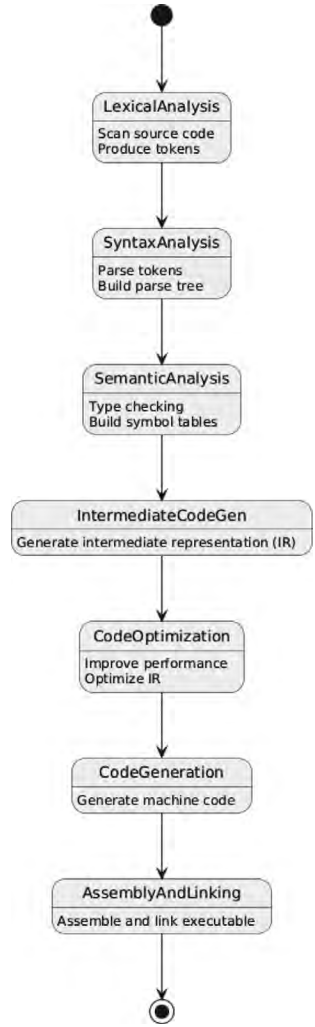



**Figure 12.1:** Compiler Phases (adapted from Aho *et al.*, 2007)

The compilation process typically involves converting the source code representation of a program into an executable form through a series of transformations (Aho *et al.*, 2007). The overall structure given in Figure 12.1 has been adapted into a unified modelling language state diagram for the purposes of this chapter.

For black box-style dynamic automated assessment tools, all phases of the compilation process are required, while for static structure analysis, only the first three will be used. For the purpose of ASTs this would require the first two (and possibly aspects of the third, should augmented syntax trees be generated) while lexical analysis would only require the first. Lexical analysis-based copy detection is more vulnerable to circumvention through superficial changes to the naming of identifiers, even if the overall logical structure of the program has been completely copied from other submissions in the set. Abstract syntax trees are resistant to such paraphrasing attempts but require the program to at least be able to be parsed in order to generate the tree. Student code submissions (especially those at foundation or first-year level) are prone to the kinds of syntax errors that would hamper tree generation.

As mentioned previously, when discussing the issues of using a reference solution for comparison purposes, there can be multiple completely valid solutions that differ significantly in terms of their logical structure. The problem of seeing if two tree or graph representations of student solutions are effectively "the same" is, at its simplest, an instance of the Graph Isomorphism Problem (which asks if one graph can be transformed into another by relabelling its nodes) and is computationally expensive to address. When one considers that students may add or remove non-crucial elements to their source code without detracting from the correctness of their solution (effectively adding or removing nodes and edges), then the problem quickly becomes intractable in the general case.

Given these algorithmic constraints and the typically severe penalties for academic dishonesty, automated assessment tools (which generally do include some form of plagiarism detection) will typically be architected in such a way as to include human-in-the-loop decision-making for the final determination, as illustrated in Figure 12.2 (Meuschke, 2023).

For AST-based approaches, the structure of the language is typically defined as a series of production rules known as a context free grammar. Consider Figure 12.3, a snippet of such a grammar from a fictional language similar to the BASIC

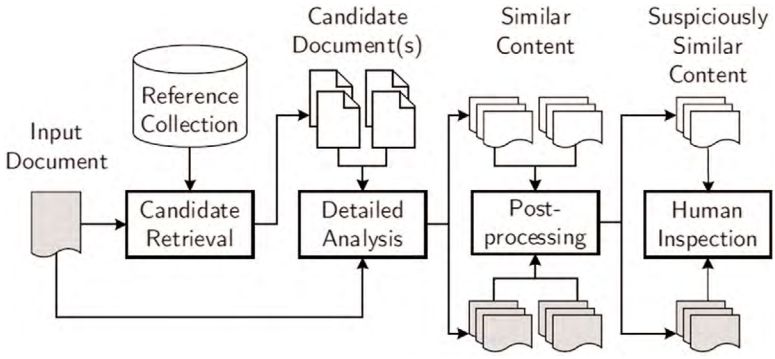



**Figure 12.2:** Plagiarism detection process (Meuschke, 2023:17)

```
<program>          ::= <statement_list>

<statement_list>   ::= <statement>
                     | <statement> <statement_list>

<statement>        ::= <assignment>
                     | <if_statement>
                     | <while_statement>
                     | <print_statement>

<assignment>       ::= <identifier> "=" <expression>

<if_statement>     ::= "IF" <expression> "THEN" <statement_list>
                     [ "ELSE" <statement_list> ] "END IF"

<while_statement>  ::= "WHILE" <expression> "DO" <statement_list> "END WHILE"

<print_statement>  ::= "PRINT" <expression>

<expression>       ::= <term>
                     | <expression> "+" <term>
                     | <expression> "-" <term>

<term>             ::= <factor>
                     | <term> "*" <factor>
                     | <term> "/" <factor>

<factor>           ::= <number>
                     | <identifier>
                     | "(" <expression> ")"

<identifier>       ::= <letter> { <letter> | <digit> }
<number>           ::= <digit> { <digit> }

<letter>           ::= "A" | "B" | ... | "Z"
<digit>            ::= "0" | "1" | ... | "9"
```

**Figure 12.3:** A sample context free grammar for a pseudo-BASIC language

(Beginners' All-purpose Symbolic Instruction Code) language family. This example was selected as a third of the modules within the Academy, making use of remote practical assessments for formative assessment, doing so using dialects of BASIC.

For simplicity's sake, this grammar only defines the portion of the language related to simple expressions, looping constructs and basic output. A grammar for a more complete language would need to be more comprehensive. Consider in Figure 12.4 a sample program (performing a simple countdown from three) written in this language:

```
WHILE X > 0 DO
    PRINT X
    X = X - 1
END WHILE
```

**Figure 12.4:** Sample Pseudo-BASIC program

Applying the production rules of the grammar in either a top-down or bottom-up manner using standard parsing algorithms (Aho *et al.*, 2007) will result in the creation of a tree structure such as is given in Figure 12.5.

Lexical analysis-based approaches, on the other hand, typically tokenise the source code into sequences of symbols appearing in the text in a given order. Such sequences are termed n-grams with n representing the length of such sequences. Bodies of text that share a large number of overlapping n-grams are likely to be plagiarised. The determination of the degree of this overlap is usually achieved by passing streams of n-grams through a one-directional hashing function which maps them onto one of a finite set of storage locations (buckets), as is illustrated in Figure 12.6. Bodies of text sharing similarly full buckets are likely to be plagiarised.

However, such techniques do not stand up to the threat posed by generative artificial intelligence. Simple previous cases of plagiarism would typically involve a small set of correct answers (whether based on previous year's practical work, student work from the current cohort, or those sourced from the Internet) would be iterated upon by cheating students creating

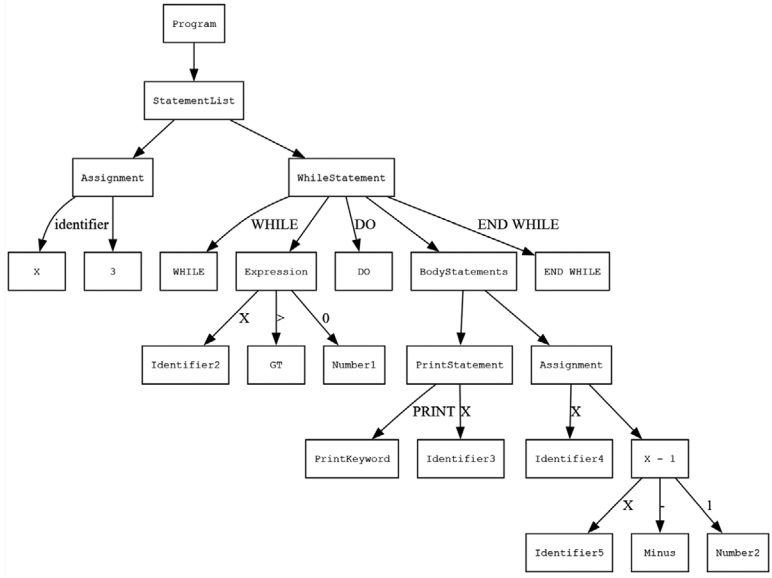



**Figure 12.5:** Tree representation of Figures 12.3 and 12.4.

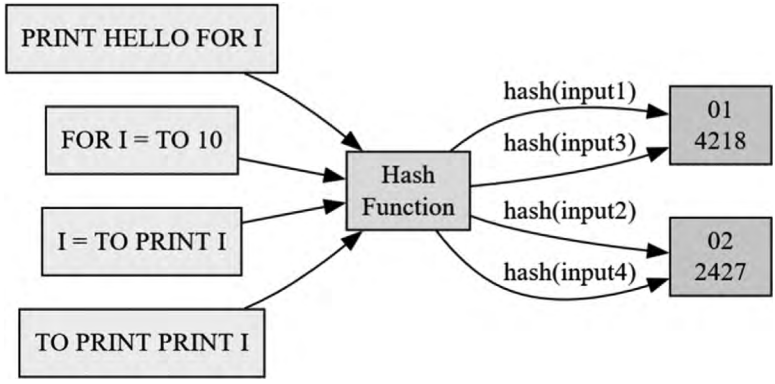



**Figure 12.6:** Hashing n-grams into buckets

dense clusters of similar work across these small-world social networks, facilitating easy detection.

**AI Threats to Assessment Integrity**

Generative AI-based academic dishonesty, on the other hand, has more in common with ghost-writing-based plagiarism, in which students would pay for bespoke solutions

to programming assignments from students outside the class or increasingly commonly from assignment-mill websites. Such cheating is at the highest end of the obfuscation scale as illustrated in Figure 12.7, making it very difficult to detect automatically.

In addition to the production of sequences of text, images, and videos that generative AI is capable of, it is well-established as being able to produce code at the level of a junior- to mid-level programmer for problem domains that are well represented within their training corpora. Unfortunately, as entry-level programming assignments are typically assessing the same competencies in similar groupings, the training data is overrepresented with such examples, making such systems especially capable of completing those tasks. Evidence exists that students are shifting away from the use of so-called "cheating hubs" such as Chegg to using generative AI and that the use of generative AI in the completion of such assignments is detrimental to learning outcomes (Chen *et al.*, 2024).

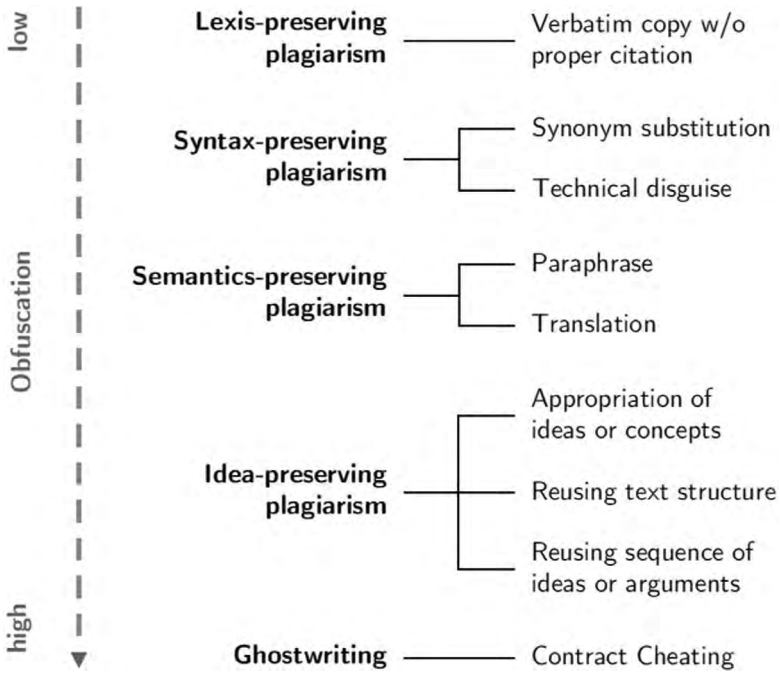



**Figure 12.7:** Plagiarism obfuscation scale (Meuschke, 2023:13)

Universities will need to update their academic honesty policies (which typically already mention the use of such contract research services) to better reflect the digital ethics of presenting generative AI outputs as their own work. As these outputs are built from the patterns extracted from analysing the creative contributions from a large number of uncredited, uncompensated, and in many cases unconsulted and unconsenting original authors.

## 2.3. Learning Style of Generative AI

It may be worth reminding ourselves that current generative AI systems are not human beings. Instead, they are pattern extraction and continuation engines that have been trained on a large proportion of the Web-accessible human cultural outputs. Therefore, they are very good at generating sequences (of text, pixels, movie frames etc) which match the patterns embedded in their training data and as those data are drawn from the output of human intellect the output of such systems closely mirrors what human intelligence is capable of (to the degree that it is represented in those corpora).

Sequence-to-sequence learning and pattern continuation algorithms are not new; however, previous techniques, such as those based on simple recurrent neural networks, were not very capable of maintaining context across long stretches of output. Initially generated sequences, such as the words responding to an opening prompt, would initially appear meaningful but would quickly degenerate into nonsense. The key insight into addressing this was the development of attention mechanisms in which the likelihood of selecting the next token for output was based on the context established by both the prompt and training data, but also the sequence of generated tokens so far (within the limits of the context window width). With each token impacting the selection of the next token, depending not only on the token itself but its position within the sequence, deeper semantic connections between tokens can be inferred from the training data.

The development of the transformer neural network architecture (Vaswani *et al.*, 2017) shown in Figure 12.8 allowed for the efficient maintenance of attention by allowing each

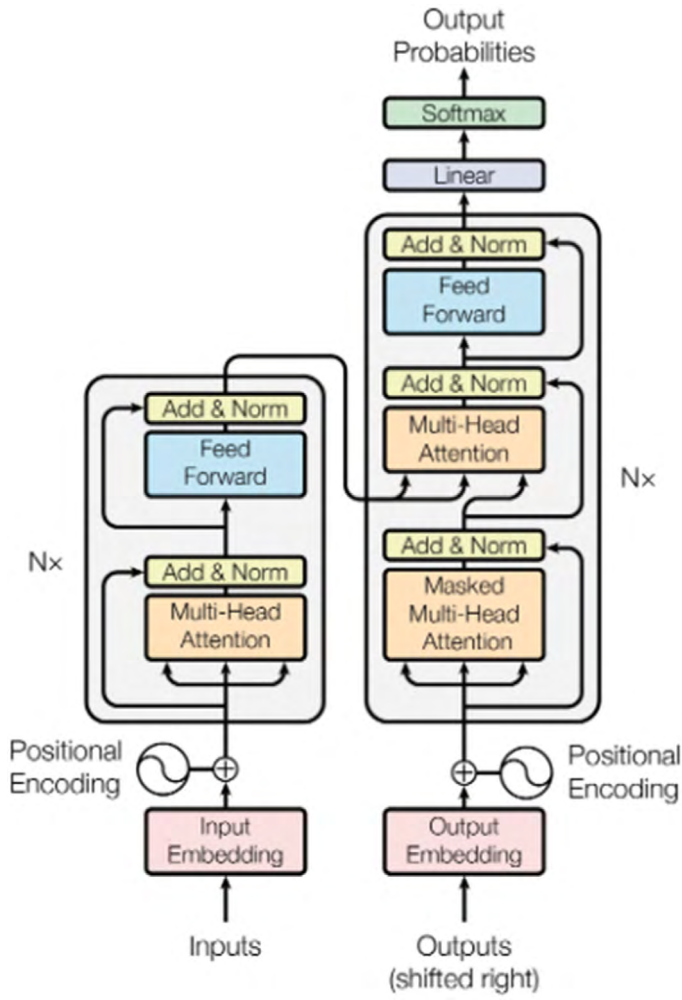



**Figure 12.8:** The Transformer architecture (Vaswani *et al.*, 2017:3).

token's contribution to be calculated independently in-parallel, as opposed to previous mechanisms which required a sequential iteration through each token's impact.

It has been shown that to capture a comprehensive model of human language, such systems as a side effect must construct a model of the world within which such a language operates. In order for such models to learn, they must be retrained on

updated corpora containing new information. This training process involves extensive iterative adjustment to the weights of the neural network (referred to as its parameters and numbering in the hundreds of billions at the present time), which is an extremely resource-intensive process. As a result, many systems will supplement their knowledge base with recent information while answering a query by injecting tokens from an external source, such as a Web-query in a process known as retrieval augmented generation (RAG) (Lewis *et al.,* 2020), which is far cheaper than completely retraining the model from scratch.

Visual information plays an important role in Software Engineering, with many aspects of the discipline requiring some ability for visual reasoning and interpretation. While it is possible for images to be generated in the sequence-to-sequence manner, textual output results were not as impressive in that domain. Modern generative AI currently largely operates on a different principle when generating images, namely through the use of diffusion models (Ho *et al.,* 2020).

Diffusion models generate images by starting with pure noise and gradually removing that noise through a learned process. This happens in two main phases. First, in the forwards process, real data (such as an image) is slowly turned into noise by adding random variations over many steps. Then, in the reverse process, a neural network learns to undo those steps, step by step, to turn noise back into a realistic image. During training, the model learns how to predict and remove the added noise. Once trained, it can generate entirely new images by starting with random noise and denoising it into something that resembles real data. In text-to-image models, like stable diffusion, a user's prompt is converted into a vector (typically using a language model), which guides the denoising process so that the final image matches the prompt. Figure 12.9 illustrates the process.

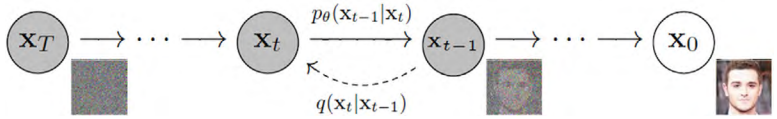



**Figure 12.9:** Diffusion based image generation (Ho *et al.,* 2020).

This disjunction between the mechanisms behind different types of reasoning (visual and verbal in this case) does not necessarily mandate that generative AI systems are not general intelligences (the consensus is that they are not, just not for that reason). The only known general intelligence (human beings) is considered within modern cognitive psychology to be composed of an ensemble of specialised intelligences (Schneider & McGrew, 2012), with the objective existence of the older concept of an underlying general intelligence (Spearman, 1904) remaining inconclusive.

## 3. Methodology

These different facets of human intelligence are reflected in certain pedagogies which emphasise the different learning styles of students, such as the widely used Visual, Auditory, Read/Write, Kinaesthetic (VARK) model (Fleming & Mills, 1992), focusing on sensory preferences. While not perfect, the VARK model is widely studied and well-understood and will be used as the basis for this work. The four learning styles within this framework are Visual, Auditory, Read / Write, and Kinaesthetic. Visual learners prefer to receive information through diagrams, charts, maps, and other visual aids. Auditory learners understand best through listening, such as lectures, discussions, or podcasts. Read or write learners engage most effectively with written text, including lists, notes, and manuals. Kinaesthetic learners grasp concepts through hands-on experiences, physical activities, or real-world examples. Many individuals are multimodal, meaning that they benefit from a combination of these styles and adapt their learning approach depending on the situation or material.

Unlike human beings, the complete mental workings of which have yet to be fully understood, we have a much better idea of the construction of generative AI systems, having built them ourselves (although their emergent properties as with all complex systems can be very difficult to predict). A reasonable working hypothesis would be that, because LLM-based generative AIs are primarily sequence-to-sequence pattern completion engines that the most natural learning style for LLMs would be a verbal (i.e. read or write) one with visual, auditory, and kinaesthetic being less capable.

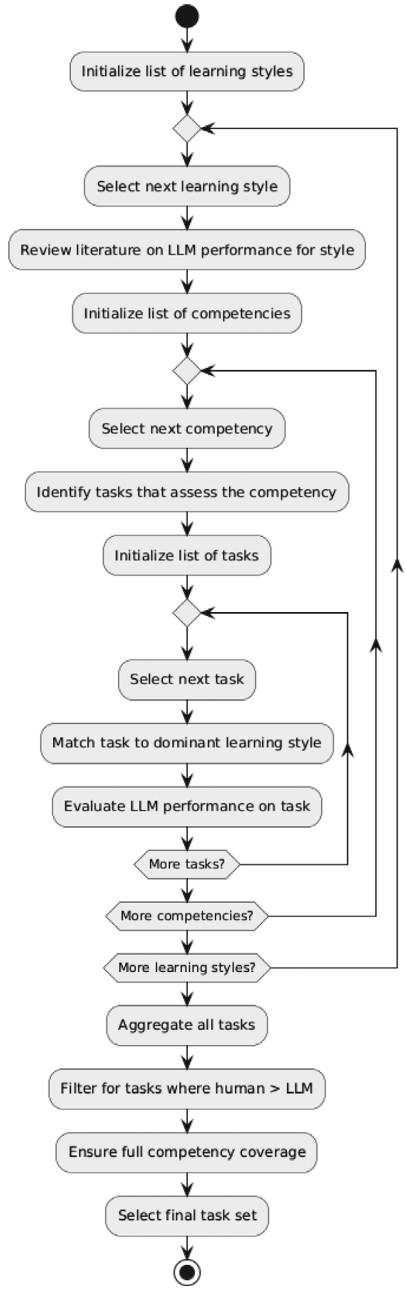



**Figure 12.10:** Plant UML activity diagram for task selection process

**Pedagogical Design Responses**

The overall approach to finding and exploiting generative AI-resistant strategies begins by iterating through each learning style, such as visual, auditory, read/write, and kinaesthetic. For each style, relevant literature is reviewed to assess how current large language models (LLMs) perform when processing or generating content aligned with that style. Next, a set of core software development competencies is identified, such as debugging, algorithm design, or API integration. For each competency, tasks that assess that specific skill are defined. Each task is then matched with the dominant learning style that it engages, and LLM performance on that task is evaluated based on existing benchmarks or experimental results. Tasks are sorted according to LLM performance within their associated learning style. Finally, tasks are selected where human performance is high and LLM performance is low, ensuring that the final selection covers the full range of competencies. This allows for a focused and balanced assessment that highlights gaps in current LLM capabilities while making use of human strengths. The process is summarised by way of a unified modelling language (UML) activity diagram in Figure 12.10.

For clarity the process follows a design-based approach in which the resulting metaheuristic is presented as a design artefact. The assessment artefacts presented are created by domain experts though there will always be a measure of interpretation required when measuring the degree of AI-resistance, and for that reason, follow-on research projects will be needed. No student data, focus groups, or surveys were used and, therefore, the requirements for ethical approval for the study were not triggered.

## 4. Results and Discussion

As an instance of the proposed strategy, consider the previously proposed working hypothesis that LLMs will perform worse on visual tasks than on verbal tasks, even if they are assessing the same underlying competency. For discussion, we will consider the computation-thinking capabilities of decomposing a high-level operation into a sequence of low-level operations (covered in first year Informatics and Computer Science modules), iteration

across collections of values (also covered in first year, first semester modules), and generalisation or specialisation through inheritance (covered in first year, second semester modules).

In order to assess this, a group of related prompts will be used per task, although each will be modified by a previous prompt dictating the nature of the output and, hence, the underlying learning style. The first task requires a visual output with the last two being textual. The second prompt allows the system to select the textual output that it deems most suitable for answering the question. The last iteration of the prompt is more detailed and provides the system with a specific textual format well-suited to the task at hand. The GPT-4o model was used as a representative example of mainstream LLMs, and its outputs were assessed by a subject domain expert. Models such as Dall-E 3, Stable Diffusion, and Midjourney were not used, as they are specialised for visual content generation, so would serve as the basis for comparison.

In order to assess both sequential reasoning and iteration across a collection of values, the task of identifying all of the even numbers in a collection was used throughout. The assessment of generalisation or specialisation reasoning was given as an extension of this task by asking for the creation of an abstract class to represent all filtering tasks with odd and even filtering classes derived from it.

Figure 12.11 shows a typical implementation of this as a virtual programming laboratory activity on the Moodle learning management system (Rodríguez-del-Pino *et al.*, 2022). The program is given in the Visual Basic programming language (used by three of the Academy's first-year modules), so in order to support this, the. NET Core toolchain was installed on the Virtual Programming Lab (VPL) Execution Jail Server, which runs and evaluates student submissions, as the programming languages supported directly by the system do not include Visual Basic. It is worth noting that only a very restricted subset of the language is used, with the usage of more advanced language features and libraries being taken as a possible indicator of improper assistance.

The following initial prompt was used following the provider's system prompt: "You will be given instructions relating

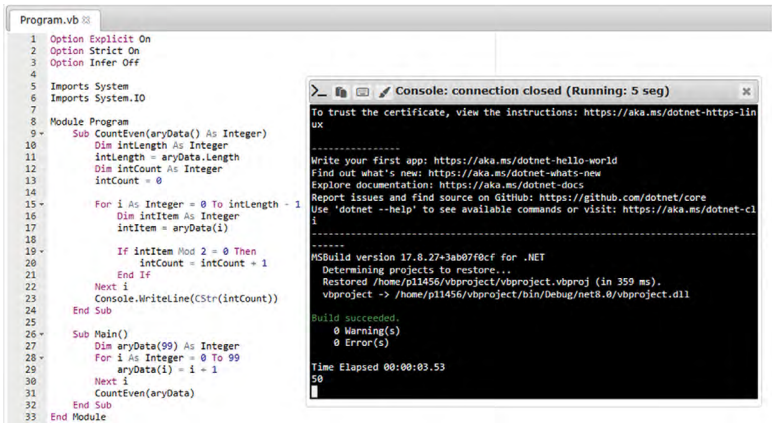



**Figure 12.11:** Reference task implementation.

to software development, each instruction has two components. The first component indicates how you are to answer a question, whether visually through image generation or textually via code generation."

The coding prompt was the following: "Answer textually. Create a Visual Basic code that counts the number of even numbers in an array" which resulted in the generation of the code depicted in Figure 12.12. It is worth noting that the less common Hungarian prefix notation used in variable naming within the Academy was not followed, and that the generation of the array used a range-based technique not covered in the module. When provided with the style guide for the module, it generated more plausible code but quickly reverted to not using the Hungarian notation, as the overwhelming majority of the code in its training corpus does not use the notation. It is worth noting that the reference solution used a subroutine while the generated code used a function, but both are allowable given the prompt. Overall, the output is both correct and plausible, but a student would need to be able to account for the use of the range and deviation from the coding standard.

The next experiment made use of a block-based visual programming language created by the University of Berkley known as Snap! (Romagosa i Carrasquer, 2019). The language can be viewed as an extension to the popular Scratch language

```
Function CountEvenNumbers(arr As Integer()) As Integer
    Dim count As Integer = 0

    For Each num As Integer In arr
        If num Mod 2 = 0 Then
            count += 1
        End If
    Next

    Return count
End Function

Sub Main()
    ' Create an array of the first 100 integers
    Dim numbers As Integer() = Enumerable.Range(1, 100).ToArray()

    ' Call the function and print the result
    Dim evenCount As Integer = CountEvenNumbers(numbers)
    Console.WriteLine("Number of even numbers in the array: " & evenCount)
End Sub
```

**Figure 12.12:** Reference task implementation.

with additional support for features more suitable for tertiary education. While the language makes use of the Lisp programming language at the back-end, it is only possible to develop solutions directly using the graphical user interface. For this reason, it was selected to compare the performance of LLMs on the same task but via their visual reasoning ability. Figure 12.13 shows the reference implementation of the task. Instead of a main subroutine, an on-click event was used, and instead of a function, a parameterised custom block was used. The components of the solution map directly onto the Visual Basic code in Figure 12.11.

The following prompt was provided to assess performance on the visual coding version of the task "Answer visually. Create a Snap! block that counts the number of even numbers in an array, show usage on an array of the first 100 integers". This resulted in the solution depicted in Figure 12.14, which is considerably worse than the fully functional code produced for the Visual Basic task. The shapes produced are superficially correct, but it relies on a non-existent even numbers parameter; it does not specify what

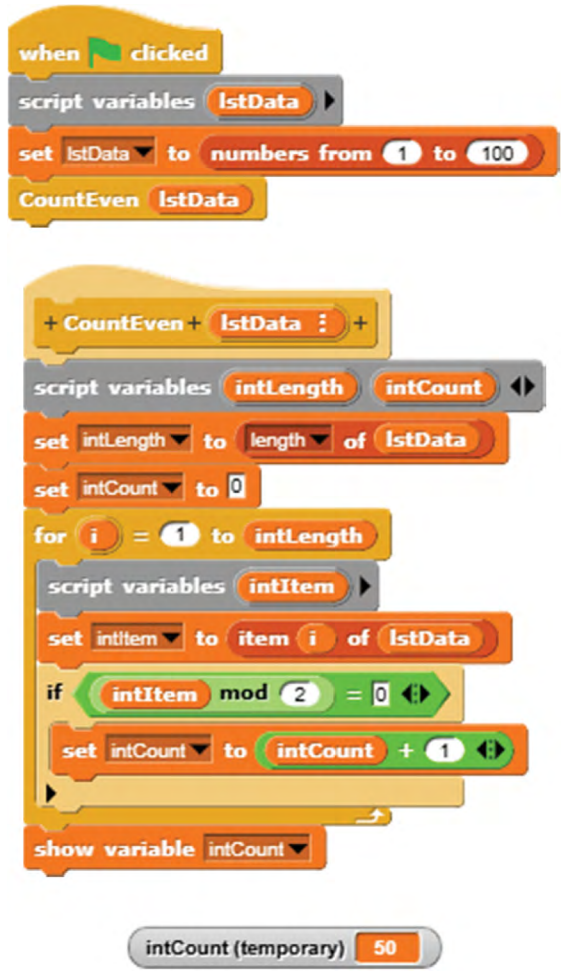



**Figure 12.13:** Reference visual programming task implementation.

container is being iterated over, and instead of a separate control block to serve as a main function, it substitutes an orphaned variable block with a very corrupted number sequence.

When prompted with the textual variant of the task via "Answer textually. Create a Snap! block that counts the number of even numbers in an array, show usage on an array of the first 100 integers" the system produced the following in Figure 12.15, which, while logically correct, is not in any way related to the

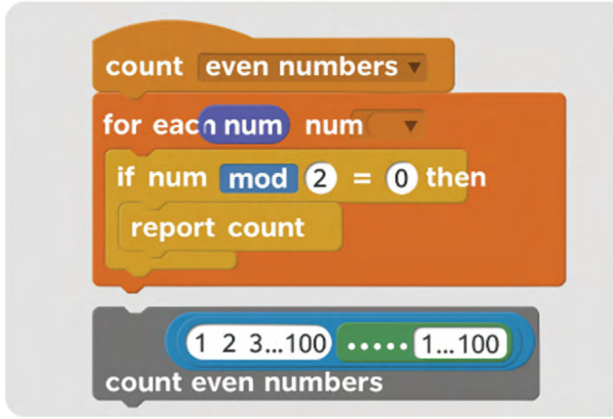



**Figure 12.14:** Generated visual programming task implementation.

Snap! Programming language. As there is no written Snap! Language, no such examples can exist in available training data and, therefore, the output is a complete hallucination.

Although direct programming in a textual manner is not possible with Snap! it is possible to export a script into an extensible markup language (XML) file, which is textual in nature. Figure 12.16 shows the XML version of the reference task depicted in Figure 12.13.

```
snap

define count even numbers (array)
    set count to 0
    for each num in array
        if num mod 2 = 0
            change count by 1
    report count
```

**Figure 12.15:** Generated textual version of visual task.

```
<blocks app="Snap! 10.7.2, https://snap.berkeley.edu" version="2">
  <block-definition s="CountEven %'lstData'" type="command" category="control">
    <header/>
    <code/>
    <translations/>
    <inputs>
      <input type="%l" initial="1"/>
    </inputs>
    <script>
      <block s="doDeclareVariables">
        <list>
          <l>intLength</l>
          <l>intCount</l>
        </list>
      </block>
      <block s="doSetVar">
        <l>intLength</l>
        <block s="reportListAttribute">
          <l>
            <option>length</option>
          </l>
          <block var="lstData"/>
        </block>
      </block>
      <block s="doSetVar">
        <l>intCount</l>
        <l>0</l>
      </block>
      <block s="doFor">
        <l>i</l>
        <l>1</l>
        <block var="intLength"/>
        <script>
          <block s="doDeclareVariables">
            <list>
              <l>intItem</l>
            </list>
          </block>
          <block s="doSetVar">
            <l>intItem</l>
            <block s="reportListItem">
              <block var="i"/>
              <block var="lstData"/>
            </block>
          </block>
          <block s="doIf">
            <block s="reportVariadicEquals">
              <list>
                <block s="reportModulus">
                  <block var="intItem"/>
                  <l>2</l>
                </block>
                <l>0</l>
              </list>
            </block>
            <script>
              <block s="doSetVar">
                <l>intCount</l>
                <block s="reportVariadicSum">
                  <list>
                    <block var="intCount"/>
                    <l>1</l>
                  </list>
                </block>
              </block>
            </script>
            <list/>
          </block>
        </script>
      </block>
      <block s="doShowVar">
        <l>intCount</l>
      </block>
    </script>
  </block-definition>
</blocks>
```

**Figure 12.16:** XML export of reference visual programming task.

When prompted with the more specific prompt "Answer textually by generating snap XML. Create a Snap! block that counts the number of even numbers in an array, show usage on an array of the first 100 integers" the system hallucinated XML output which, while valid, (in that it conforms to the requirements of the XML standard) does not represent an importable script.

In addition to code generation, the system was prompted with the visual algorithmic design task of creating a behavioural model of the problem using a UML activity diagram. Figure 12.17 shows the reference answer for the task.

The system was prompted with "Answer visually. Create a UML Activity Diagram for a system which counts the number of even numbers in an array" resulting in the diagram shown in Figure 12.18. The output does not seem to be correctly showing any form of looping (it incorrectly creates an activity node that has the word "for" in it rather than having a transition back to a predecessor node. The logic for incrementing the count is completely reversed and will instead count all of the odd numbers.

Figure 12.19 shows the results of allowing the system to generate textual output for the visual task by way of allowing it to make use of the GraphViz DOT format and PlantUML format, respectively. Both of these are textual languages dedicated to the specification and visualisation of graph structures, with PlantUML being more focused on software engineering diagrams. As with the programming task, allowing the system to output textual results to a visual question did not significantly improve

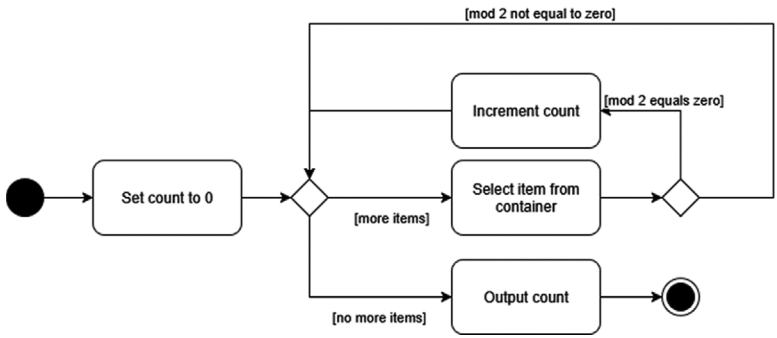



**Figure 12.17:** Reference answer for the algorithm modelling task.

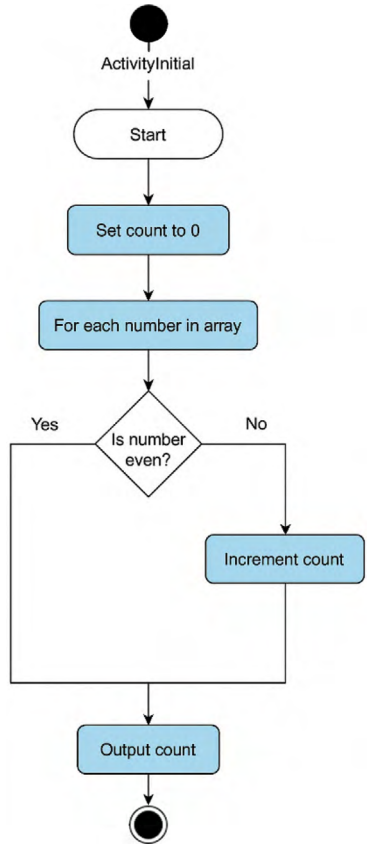
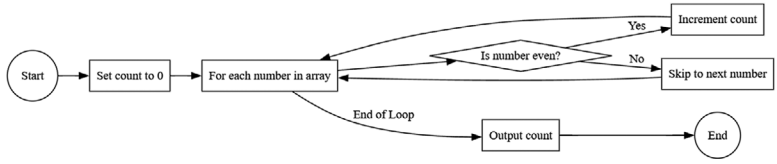



**Figure 12.18:** Visual algorithmic modelling result.

its performance. Both fail to capture the nested iteration by way of multiple decision nodes linking back to predecessor states and rely on erroneous "for" activities.

Figure 12.20 shows the reference solution for the generalisation or specialisation task. The task was presented as follows: "Design a system in which a parent filter class with an abstract filter method is specialised into an EvenFilter and



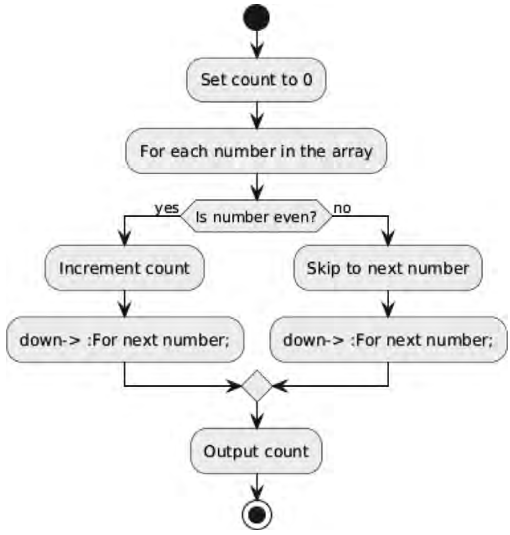



**Figure 12.19:** Rendered textual outputs for the visual modelling task.

OddFilter class. The method operates on an array of integers and outputs those that pass the test."

Figure 12.21 shows the graphical response to the task. The structure is largely correct; however, the definition of the array and function types contains a syntax error. The placement of the abstract stereotype within the attributes compartment of the base filter class is also in error.

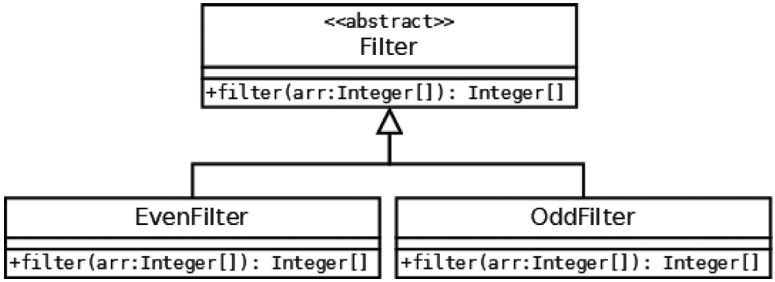



**Figure 12.20:** Rendered textual outputs for the visual modelling task.

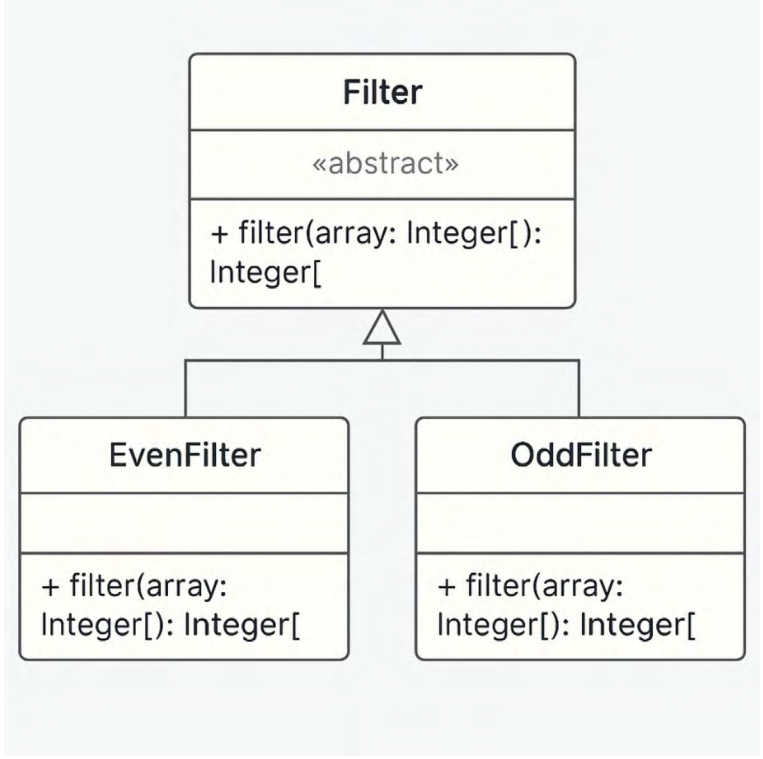



**Figure 12.21:** Rendered textual outputs for the visual modelling task.

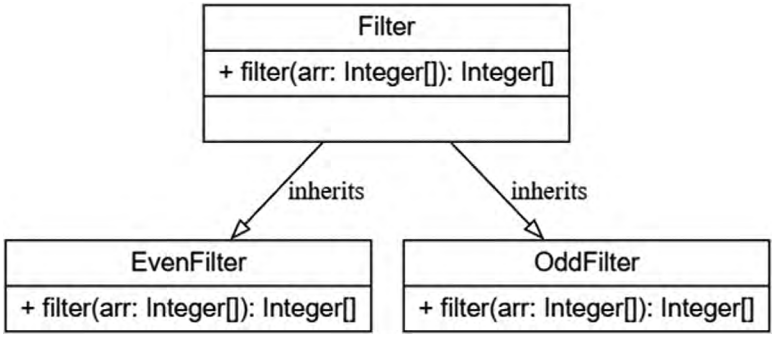



**Figure 12.22:** Rendered textual outputs for the visual modelling task.

Figure 12.22 shows a textual response to the generalisation or specialisation task where the system was allowed to respond with textual Graphviz DOT output. In this case, there are surprisingly

more errors, but they are different from those produced when graphical output was requested directly for the same task. The definition of the methods, their parameter types, and return types is correct. However, the base Filter class has its method placed in the attribute compartment and the generalisation arrows are pointing in the wrong direction. The use of the explicit "inherits" text is a bit odd because the arrowhead automatically indicates the nature of the relationship. The omission of empty compartments in the derived classes but not the base class is also inconsistent.

The following discussion concerns the previously presented results.

The emerging pattern of these results highlights the fact that human cognition and generative AI competencies are not fully aligned despite the intended design goal of such systems being the creation of plausibly human generated data. For this reason, interstices exist in which authentic human assessment remains possible with systematic exploration of the assessment space.

In the same manner as extensions for Bloom's Taxonomy have been created within the computing domain (ACM Committee for Computing Education in Community Colleges, 2023) so too could a version of Bloom's Taxonomy for AI-resistance be constructed. By simultaneously measuring an assessment against both activities can be selected which cover the correct range of conventional taxonomy levels while remaining high on the AI-resistance scale.

The world of work is becoming increasingly AI-integrated so to better reflect that reality it is worth considering that AI-resistance should not be the ultimate goal of all assessment design. Contrapuntally, mathematicians are not employed to solve calculus or algebra problems but they must understand those tools to solve more complex ones. The only way for them to gain that competency is via authentic assessment of their abilities and attainment rather than by integrating wolfram alpha into their exams.

In terms of access in the South African and broader Global Southern context it is worth considering the potential gains in terms of access that students with more limited computer competency may gain through AI-integrated versus AI-resistant

assessment. Such trade-offs would need to be carefully considered.

AI-resistant assessment design is, therefore, not to be confused with resistance to AI in general. It forms part of the holistic view of education in the context of the Fourth Industrial Revolution. In the same way that automotives reduced the exertion and skills requirements for travel they did not replace the need for healthy physical activity. Sometimes we will need AI-assistance, sometimes we must walk alone. To do so we need to be able to define tasks that are well-suited for building human capacity and ill-suited for AI completion.

## 5. Conclusions and Practical Applications

The chapter explored the possibility of exploiting asymmetries in the capabilities of generative AI to select tasks for which such systems perform worse while assessing the same competencies. A series of research questions were posed to explore the issue. These will now be revisited and answered as much as is possible.

- RQ1: Are monitoring and detection viable strategies for remote assessment in the age of generative AI? The literature view indicated that, by themselves, monitoring and detection are not viable strategies for ensuring authentic assessment.
- RQ2: Is there evidence to suggest that cognitive impairment occurs in software development tasks as a result of over-reliance on generative AI? The literature review revealed that evidence of a reduction in cognitive capabilities is associated with an over-reliance on generative AI.
- RQ3: What is the learning style of modern generative AI? The exploration of the differences in performance between visual and purely textual tasks indicated that, according to the VARK model, LLM systems would count as Read/Write learners.
- RQ4: Are there tasks that measure the required aptitudes for software development that humans perform well on that current generative AI does not handle well? The result of answering RQ3 was supported through the exploration of the performance of such systems across a variety of visual and verbal software engineering tasks, which showed reduced performance on visual tasks. This work would need to be

extended to incorporate a wider variety of learning styles and a more comprehensive battery of assessments.

- RQ5: How sensitive is LLM performance to the provided prompt in Software Engineering tasks? The exploration suggests that they are very sensitive to the wording of the prompts, as novel errors occurred when the output format was specified.
- RQ6: What strategies can be derived from the answers to the previous research questions to facilitate online assessment? Figure 12.10 illustrates a process for identifying suitable tasks.

The process given in Figure 12.10 is not guaranteed to be a permanent solution to the issues of generative AI and assessment in software development modules. If AI capabilities continue to improve, the gap between different learning styles will narrow, and if it reaches the point where even those capabilities for its weakest learning style exceed the learning outcomes of a module, then AI will remain an attractive mechanism for cheating in spite of selecting tasks by learning style. Work is still ongoing in determining how AI can be incorporated into assessment for software development without undermining the skills required to hold the output of such AI systems to account. The following discussion interprets the results.

As mentioned previously it is important to strike a balance between developing the tools required for designing assessments best suited for human completion and the advantages gained by the appropriate use of AI-integrated assessment. Ironically, it is the more low-level practical tasks given to students at lower NQF levels, which are easier for AI to complete within Computer Science education, such as the implementation of known algorithms and data structures which are probably best left to unaided humans in order to develop the neural pathways supporting more advanced thinking. This foundation, though easy to omit, is crucial to address the junior to senior pathway problem experienced in industry.

Should these strategies prove viable it would be necessary to integrate them into the professional development of upcoming Computer Science educators in the same way as learning management and remote assessment design already has been.

## 6. Acknowledgements

As generative AI was the subject of the investigation, it was used in the preparation of some of the diagrams in this chapter. AI-adjacent technology was used for language checking and editorial purposes.

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Chapter 13

# Equipping South African IT Graduates for Success in the Modern Workforce

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## Abstract

In the continuously evolving landscape of information technology (IT), it is imperative for educational institutions to prioritise the preparation of graduates for the workforce, particularly within the South African context. The notable gap between academic curricula and the expectations of industry has emerged as a significant challenge, resulting in IT graduates frequently being inadequately equipped with the essential skills and competencies that employers demand. This chapter proposes a comprehensive framework aimed at enhancing the employability of IT graduates by strategically aligning educational practices with industry needs. The proposed framework advocates for an integrated approach that effectively combines experiential learning opportunities, industry collaboration, and the development of essential soft skills within the educational curriculum. Additionally, this study aims to identify critical areas for improvement, such as the incorporation of emerging technologies into teaching methodologies, the necessity for increased collaboration with industry stakeholders, and the importance of ongoing curriculum assessments to adapt to the

rapidly changing technological environment. This research attempts to not only bridge the existing skills gap but also to cultivate a more resilient and robust framework of industry-ready professionals in the South African IT sector, thereby fostering a workforce that is better aligned with the demands of a dynamic global economy.

**Keywords:** 4IR, IT graduates, soft skills, work readiness

## 1. Introduction

The South African higher education landscape has experienced a significant shift to align with global developments, where these developments are characterised by an increased emphasis on market forces that have created students as consumers and university faculties more as service providers (Fru *et al.,* 2024). Research has indicated that many recent graduates lack the necessary competencies, including skills, abilities, and experience, to successfully navigate and thrive in the dynamic labour market (Magagula *et al.,* 2020). The evolving relationship amongst universities, students, and employers has been emphasised by Boden and Nedeva (2010), who assert that employers increasingly prioritise the recruitment of work-ready graduates over the training of new hires (Boden & Nedeva, 2010). This view is supported by Masole and van Dyk (2016), who argue that numerous graduates seem inadequately prepared for the demands of the workforce, thus leading to more experienced hires in the workplace. The discontent amongst employers regarding graduates' work readiness (WR) highlights two critical concerns. First, possessing field-specific knowledge and technical skills alone is insufficient to categorise graduates as work-ready. Second, there is a pressing need for graduates to cultivate additional competencies beyond their formal education that will empower them to effectively manage the stresses inherent within the workplace environment (Masole & van Dyk, 2016). As South Africa grapples with the challenges of the Fourth Industrial Revolution (4IR), addressing the gaps in work readiness amongst IT graduates becomes even more crucial to fulfilling the expectations of employers and ensuring that the workforce is prepared to adapt and thrive in an evolving job market.

South Africa (SA) is currently navigating the 4IR landscape, and according to Levin (2018)., while showing promise in Industry 4.0, there are significant risks and challenges that must

be negated in SA (Levin, 2018). The biggest challenges in Africa remain connectivity and accessibility, as well as insufficient skills (Levin, 2018). Students are known to adopt a more pragmatic perspective when choosing to pursue higher education. They typically hope that their degree will equip them for the workforce and enhance their job prospects (Valstar *et al.*, 2020). Given the need to prepare graduates in South Africa, specifically in the Information Technology (IT) sector, it is crucial to investigate the work readiness of South African IT graduates. The rapid evolution of technology demands that these graduates not only possess theoretical knowledge but also practical skills that align with industry requirements. Employers are increasingly expressing concerns about the preparedness of graduates to meet the technical and soft skills needed in a dynamic work environment. This study aims to assess the gaps between educational outcomes and industry expectations, in an attempt to identify strategies to better equip graduates for the workforce within the IT sector. Addressing this gap is vital, as a well-prepared workforce is integral to using the opportunities presented by the 4IR and ensuring sustainable economic growth in South Africa.

This study will continue by examining some of the issues currently faced by graduates' work readiness within the IT sector in Section 2. Having understood the gaps, a proposed framework will be presented in Section 3 that outlines the steps taken to help better prepare IT graduates for the workplace. Finally, it draws on our conclusions from the presented framework and future works in Section 4.

## 2. Literature Review

Contrary to what students anticipated, numerous Computer Science or IT graduates find themselves ill-equipped to tackle the hurdles presented by their initial employment (Craig *et al.,* 2018; Begel & Simon, 2008). The gap between academic training and the practical demands of the industry in Computer Science or IT was highlighted over two decades ago, as indicated in previous research (Lethbridge, 1998). Nevertheless, research from the last ten years suggests that little advancement has been made in bridging this divide. This persistent issue emphasises the need for a more integrated approach to education that aligns more

closely with the evolving requirements of the tech industry, specifically within SA. Notably, many students accepted into the IT programme at the University of Johannesburg possess little to no computer literacy, further emphasising the necessity to equip graduates with the skills essential for a smooth transition into the IT sector.

Globalisation, increased competition, rapid technological advancements, the massification of higher education, and the evolution of the knowledge-based economy have heightened the demand for constantly improving workforce capabilities in a fast-changing world. The swift pace of technological change and the quick obsolescence of knowledge have led to significant shifts in job structures and skills requirements (Mainga *et al.,* 2022). As a result, organisations are seeking a more capable workforce that can navigate the growing complexities of the workplace. The need for increased work readiness has raised important questions about the quality and readiness of graduates entering the job market from tertiary education, which ultimately places unwanted pressure on graduates (Mainga *et al.,* 2022). In light of the increasing rates of graduate unemployment and under-employment, the employability skills of recent university graduates have emerged as a significant concern for university administrators, employers, government agencies, graduating students, and other relevant stakeholders. Despite the increasing interest in the topic, most studies published on employability skills have primarily focused on developed and advanced developing nations (Mainga *et al.,* 2022).

As a result, universities globally are facing demands to prepare graduates who are ready for employment. While many institutions have responded to this challenge, the advancements made have been inconsistent and have faced various obstacles. A study by Mtawa *et al.,* (2021), looks at enhancing graduate employability attributes and capabilities formation, which can be seen as a service-learning approach. The study argues for the use of community service-learning (CSL) as a pedagogical tool to bridge the gap between academic learning and the workplace, particularly within the South African higher education context (Mtawa *et al.,* 2021). Drawing from the Capability Approach,

the authors critique the narrow, skills-based conception of employability and instead advocate for a more holistic model that cultivates both technical and humanistic attributes, such as critical thinking, teamwork, communication, agency, and social responsibility. The key advantage of CSL is its capacity to foster experiential, reflective, and transformative learning that aligns graduates not only with employer expectations but also with broader societal needs for inclusion, empathy, and civic engagement. However, the study acknowledges limitations, including the resource-intensive nature of CSL, uneven student benefits, and potential epistemic injustice between students and communities (Mtawa *et al.*, 2021). A major gap lies in the under-application of CSL in "hard" disciplines like IT, where its potential to develop essential workplace readiness and ethical reflexivity remains underexplored, thus offering fertile ground for future research and curriculum innovation within the IT sector.

The Capability Approach, originally developed by Amartya Sen and further expanded by Martha Nussbaum, shifts the focus from narrow skills acquisition to the expansion of individuals' real freedoms and opportunities to act in ways that they have reason to value. In the context of higher education, this approach moves beyond a checklist of employability skills and instead asks: what kinds of graduates are we enabling students to become? Capabilities such as agency, critical reasoning, social awareness, and the ability to engage meaningfully with societal problems are highlighted. Thus, employability is reframed not merely as labour market readiness, but as the development of empowered, reflexive, and socially responsive professionals. In this chapter, the project-based and Projects Day framework can be interpreted through this lens: the emphasis on real-world problem identification, stakeholder engagement, iterative feedback, and public presentation does not merely build skills, but expands students' capabilities for agency, communication, collaboration, and ethical decision-making within complex socio-technical systems.

In research conducted by Butin, the concept of service learning, typically defined as the connection between academic study and community service, is examined critically (Butin, 2006).

This approach has gained support from two complementary movements: the government's push for civic engagement and the public's increasing demand for higher education to offer more significant and relevant experiences and outcomes for students (Butin, 2006). While service learning is widely celebrated for linking academic content with civic engagement and positively impacting student development, Butin argues that it has been insufficiently critiqued and remains marginalised within traditional academic structures. Butin's study highlights the field's blind spots, such as rigid notions of reciprocity, the problematic "server / served" dichotomy, and unexamined assumptions about power and pedagogy. Furthermore, Butin's study proposes bold alternatives, including rethinking service learning without service, as community, as Science, or as part of formal academic disciplines like Community Studies. The opportunity to enhance the transformative power of service learning, promote students' agency, and integrate it more firmly within academic institutions is also emphasized (Butin, 2006). However, disadvantages include the potential dilution of its egalitarian ethos, institutional resistance, and the risk of over-academicising grassroots engagement. A key gap to exploit lies in reconceptualising service learning for hard disciplines like IT, not just as outreach but as integrated, critical pedagogy that interrogates power, identity, and real-world application, which is a recognised approach to service learning known as critical service learning.

A study by Mainga *et al.,* (2022) offers an in-depth examination of the alignment between employers' expectations and the perceived preparedness of graduating business students in Papua New Guinea. Using a triangulated survey of employers, lecturers, and students, the study reveals that while all stakeholders value core soft skills, particularly communication, teamwork, and problem-solving, employers rank these skills significantly higher than students, pointing to a persistent perception gap (Mainga *et al.,* 2022). Moreover, although academic and discipline-specific competencies were generally seen as well-developed, there were notable discrepancies in perceptions of personal management skills, such as perseverance and initiative, with employers rating them more favourably than

the students themselves. One notable finding is that students tended to underestimate their own soft skills development, which may hinder their ability to confidently articulate employability in job interviews. The study also exposes the limitations of lecture-centric teaching methods being still dominant in many developing contexts (Mainga *et al.*, 2022), finding them insufficient for cultivating the nuanced soft skills required in contemporary workplaces. In their study, an interesting finding was their multi-stakeholder approach, which is constrained by its small sample size and focus on a single institution. There is, thus, a valuable gap to exploit by applying this triangulated perceptual method across multiple faculties and universities, especially in technical disciplines like IT, to examine how varied pedagogies affect soft skills formation.

**Table 13.1:** A summary of the key themes, findings, gaps and frameworks presented in the existing literature.

| Theme | Key Findings | Gaps to Exploit | Framework/ Model |
|---|---|---|---|
| Academic-Industry Gap | Persistent misalignment between IT education and workplace demands | Curriculum redesign aligned with real-world IT tasks | Non-specific, but emphasises curriculum-industry alignment |
| Soft Skills Deficit (Mainga *et al.*, 2022) | Communication, teamwork, and initiative undervalued or underdeveloped in graduates | Systematic soft skill development in IT degrees | Graduate Employability Skills Framework (soft skills emphasis) |
| CSL (Community Service Learning) (Mtawa *et al.*, 2021) | CSL promotes critical, reflective, and social learning for workplace prep | Implement CSL in tech fields to build workplace reflexivity | Capability Approach, Experiential Learning through CSL |

(*Continued*)

**Table 13.1:** A summary of the key themes, findings, gaps and frameworks presented in the existing literature. (*Continued*)

| Theme | Key Findings | Gaps to Exploit | Framework/ Model |
|---|---|---|---|
| Service-Learning Critique (Butin, 2006) | Traditional service-learning lacks depth in hard disciplines like IT | Apply critical service learning in IT curriculum | Critical Pedagogy, Community as Science |
| Perception Gap in Skill Readiness (Mainga *et al.*, 2022) | Employers rate skills higher than students do, especially in soft skills | Extend triangulated perception studies to IT across SA | Triangulated Stakeholder Perception Analysis |
| Teaching Method Constraints | Lecture-based methods insufficient for soft skill development | Pedagogical reform to move beyond passive learning in IT | Active vs Passive Learning Models in Developing Nations |
| WIL Framework (Ferns *et al.*, 2019) | Ten domains critical for employability and the importance of partnerships | Apply the WIL framework in more IT driven fields | Collaborative, Partnership, Group based for Employment Framework |

Other research has pointed out the benefits of enhancing graduate employability through a collaborative, stakeholder-driven framework grounded in work-integrated learning (WIL). A study by Ferns *et al.*, (2019) presents a mixed-methods approach, multi-case analysis of Chemical Engineering, Occupational Therapy, and Primary Education in Australia, which identifies ten core domains critical for employability development. These core domains include WIL, curriculum design, staff expertise, professional identity, and transition to work. A key strength

of the study lies in its proposal of a WIL Partnerships for Employability Framework, which redefines collaboration to include institutional leaders, teaching staff, employers, students, graduates, and professional bodies (Ferns *et al.*, 2019). The framework emphasises co-designed, authentic curriculum and feedback-rich environments as essential for preparing students for complex, evolving workplaces. Notably, the study critiques restrictive university policies and fragmented partnerships as significant barriers, calling for more agile institutional cultures and inclusive, trust-based collaborations. While the study robustly highlights the value of experiential learning and cross-sector dialogue, its focus on accredited, practice-oriented disciplines may limit generalisability to fields like IT. This presents an exploitable gap in adapting and testing the WIL framework within less-regulated, innovation-driven domains that could yield new insights into scalable, discipline-agnostic (Ferns *et al.*, 2019).

The existing literature highlights significant disparities in IT education and workforce readiness, particularly within the South African IT sector. Many studies point to a gap between theoretical knowledge and practical skills, resulting in graduates who are unprepared for the demands of the workplace. Furthermore, there is a noted deficiency in soft skills, such as communication and teamwork, which are crucial for professional success. The findings, gaps and frameworks presented in these existing studies can be seen in Table 13.1. Our framework aims to address these gaps by integrating hands-on learning experiences, such as project-based coursework, and an annual Projects Day event where the students can network and present their work. By fostering collaboration with industry partners, we will ensure that our students not only master technical competencies but also develop the essential soft skills necessary for thriving in a dynamic work environment. Through targeted initiatives and a restructured educational approach, our framework seeks to create well-rounded IT graduates equipped to meet the specific challenges of the South African job market. Having noted the gap in related skills and the difficulties in transitioning to industry, the University of Johannesburg, Academy of Computer Science

and Software Engineering, is dedicated to bridging this gap and is focused on ensuring that students are ready to transition from academia to industry. This study will delve into the proposed framework that will encompass the different steps taken to prepare students for the IT sector, specifically our organised group projects and annual Projects Day event.

## 3. Framework

This study seeks to enhance the preparedness of IT graduate students for the professional landscape within a South African context. It presents a comprehensive framework implemented at the Academy of Computer Science and Software Engineering, specifically designed for final-year undergraduate students, as shown in Figure 13.1. This framework encompasses a detailed examination of the year-long projects, as well as the Projects Day event. Additionally, the study will compare these elements with existing literature to emphasise the associated benefits, thereby contributing to the discourse on effective educational strategies in Information Technology.

The year project is a multilayered process as identified in Figure 13.1, which is broken down over two semesters, comprising of 27 weeks. The multilayered approach involves the projects process and the Projects Day process. Our Projects Day initiative is to take professional development a step further by requiring students to create three-to-four person teams to develop a three-tier system throughout the year that addresses real-world problems. Students are tasked with finding sponsors for their problem statements, which aims to simulate the client interaction that they will inevitably experience in the professional world. The process of conducting interviews, extracting requirements, and documenting the design and development of the project is invaluable for building project management and problem-solving skills. The project's stages, including Alpha, Beta, and final reviews, help students to understand the importance of quality control, project milestones, and client satisfaction in a professional context. This complex, year-long project mirrors the challenges that they might face in their future careers in industry.

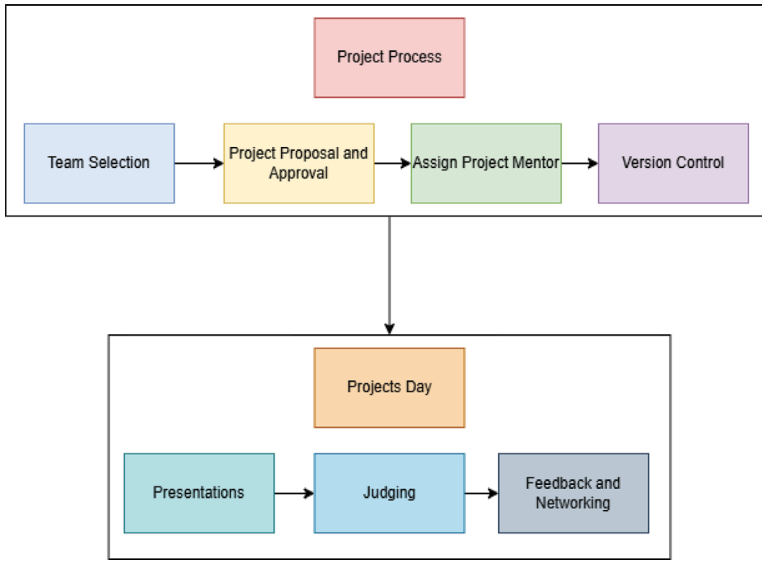



**Figure 13.1:** A figure that highlights the overview of the framework, which illustrates the project process and the Projects Day initiative.

## 3.1. Project Process

The project process involves the following steps: team selection, project proposal and approval, project mentoring and version control. Each step will be examined to illustrate how the process works and the potential benefits that it may yield.

While traditional community service learning (CSL) has often been associated with civic or nonprofit engagement, this framework adopts a broader conception of "community." In the context of Information Technology education, community includes industry partners, small businesses, startups, public sector organisations, and users affected by technological systems. By expanding the notion of community beyond charitable service to socio-technical ecosystems, the project process aligns more closely with critical service learning, where students engage with authentic societal and industry stakeholders while interrogating the social impact of technological design.

### *3.1.1. Team Selection*

Students are split into teams, which consist of a maximum of four members. The students will have the option to choose their own team, and if they are not associated with a specific team by a predetermined cut-off date, they will be allocated to a team by the Project Coordinator. When forming a team, several practical considerations should be taken into account, and the following is advised to the students:

- Select team members whose skills and knowledge complement one another.
- Choose members who share similar interests.
- Include individuals who are motivated to contribute.

Additionally, a team leader must be appointed to coordinate activities, communicate with the mentor, and submit all deliverables. It is crucial for team members to recognise that collaboration is essential for success; a lack of cooperation from any member can adversely impact the entire team. Following the submission of each deliverable, the contributions of each team member will be evaluated when allocating marks. The collective effort of the team is vital in navigating any challenges that arise during the project's development lifecycle. Members must not only apply their technical knowledge in software development but also engage in effective project management and foster positive team dynamics. The team selection process outlined offers several key benefits that specifically prepare students for the workplace.

Allowing students to choose their own teams engages them in a crucial aspect of professional life, specifically collaboration; however, it is noted that in the usual workforce, this is not a commonality, and in many cases, employees are forced to work with the members in their team. It mirrors real-world scenarios where diverse skills sets create stronger teams and emphasises the importance of assembling groups with varied strengths. Focusing on shared interests enhances commitment to team success, mirroring workplace dynamics that foster productivity and job satisfaction. This practice builds essential interpersonal skills like communication and conflict resolution, as mentioned by Butin (2006). Appointing a team leader simulates managerial

roles, helping students to develop leadership, decision-making, and accountability skills. Evaluating individual contributions fosters responsibility, as each member's performance directly impacts the team's outcome. Overall, these team selection guidelines equip students with practical skills that align with the demands of the modern workplace, preparing them for successful futures.

### *3.1.2. Project Proposal and Approval*

It is mandatory for each team to secure an industry sponsor relevant to their chosen project. Emphasising the significance of practical application, it is crucial that the projects undertaken are industry-oriented and aimed at solving real-world problems. Ideally, the project sponsor will present a challenge that can be effectively completed by a group of four undergraduate students within an eight-month period. When selecting the projects, the students are made to consider the following: industry need, specific business processes, scalability and social context. Once a sponsor is found, teams are required to book an appointment with their assigned project mentors. In cases where teams fail to find a project sponsor, mentors will aid the teams in finding a problem.

Securing an industry sponsor for projects greatly benefits students by preparing them for the workplace in several ways. Firstly, in real-world experience, students tackle actual business challenges, gaining practical knowledge that is crucial for their future careers, which addresses Maginga *et al.*,'s study, which emphasises the need for students to understand employers' expectations (Mainga *et al.*, 2022). The second benefit comes in the way of networking; engaging with industry sponsors helps build professional connections, paving the way for internships and job opportunities. Engaging with industry sponsors through networking significantly prepares students for the workplace. It helps them to build valuable professional connections that provide insights into industry trends and expectations. These interactions often lead to internships and job placements, which are critical for gaining hands-on experience and applying academic knowledge. This networking facet is particularly dominant on the Projects Day. The third benefit allows students to understand business processes, by focusing on specific industry needs, students

learn how organisations operate, enhancing their marketability. Additionally, students learn teamwork skills; collaborating on complex projects fosters essential teamwork and communication skills needed in any job setting, which was a key finding by Mtawa *et al.,* that addresses the capability approach (Mtawa *et al.,* 2021). The next benefit can be seen in the way of scalability and impact awareness; students develop an understanding of the broader implications of their work, which is valuable to employers. Finally, mentorship, where guidance from project mentors provides constructive feedback, simulating workplace relationships and preparing students for future supervision. Overall, this step equips students with practical skills and confidence, making them more employable in their careers.

### *3.1.3. Project Mentors and Meetings*

The role of the project mentor is to act as a guide or mediator or consultant for the teams. Project mentors are responsible for advising on and approving potential project proposals and providing expert advice on various project stages, including analysis, design, implementation, and testing. Weekly meetings are set up to monitor progress, assess each team member's contributions towards the project, and identify any team-related issues. The involvement of a project mentor plays a crucial role in preparing students for the workforce, as highlighted in the literature review section of our study. By acting as a guide, mentors provide students with invaluable insights into real-world project dynamics, bridging the gap between academic theory and practical application. This mentorship fosters essential skills such as critical thinking, problem-solving, and effective communication, key competencies sought by employers (Magagula *et al.,* 2020; Butin, 2006). Weekly meetings with mentors not only facilitate ongoing feedback but also encourage accountability amongst team members. This mirrors workplace environments where regular check-ins and collaborative efforts are vital for project success. Students learn to articulate their contributions, address concerns, and collaboratively navigate challenges, akin to what they will experience in a professional setting. Furthermore, mentors help students to refine their project proposals and advise on various stages of the project

lifecycle. This aligns with workplace expectations where employees often need to present ideas and receive constructive criticism. Such experiences enhance a student's capacity to adapt to feedback and implement changes, which is a critical aspect of professional development.

### *3.1.4. Version Control*

Version control has been actively used in the software development community for many years. Its main purpose is to keep track of different versions of the solution being developed. Along with this, it keeps track of each developer's changes and contributions. The main advantage of version control is the ability to develop independently. Version control plays a crucial role in preparing students for the workplace by equipping them with essential skills that are highly valued in the software development industry. By familiarising students with version control systems, they learn to manage their projects more efficiently and collaborate effectively, mirroring real-world practices (Zolkifli *et al.,* 2018). One key benefit of version control is that it promotes independent development, allowing students to work on their tasks without interfering with others' contributions. This mirrors industry standards where developers need to independently develop features while maintaining a cohesive product. Furthermore, it helps students to understand the importance of documenting changes and tracking progress, which is essential in a professional environment, as highlighted in the literature review.

Version control teaches students important skills such as problem-solving and critical thinking. They learn to navigate and resolve conflicts that may arise from multiple changes, enhancing their ability to work in teams and manage project timelines. This practice not only builds their technical proficiency but also their interpersonal skills, making them more attractive candidates to potential employers, which is a gap that is identified in existing literature (Butin, 2006). Moreover, the use of version control systems fosters a culture of accountability and transparency. Students become accustomed to the review and feedback processes, which are integral to workplace dynamics. This aligns with findings from the literature review that emphasise

the importance of peer reviews and collaborative feedback in professional settings. In summary, incorporating version control into students' learning experiences not only equips them with practical technical skills but also prepares them for the collaborative and dynamic nature of the workplace, ensuring that they are ready to meet the demands of future employers.

The project process aims to enhance the employability of IT graduates in South Africa by implementing a comprehensive strategy that bridges the gap between academic learning and workplace requirements. It begins with aligning the curriculum to current industry standards through collaboration with experts to identify critical skills gaps. The project incorporates hands-on experience through real-world projects, enabling students to apply theoretical knowledge in practical settings. Emphasis is also placed on soft skills development through workshops focused on communication, teamwork, and problem-solving, which are essential in the collaborative IT environment. Additionally, students are paired with industry and academic mentors for guidance and networking opportunities, helping them to build professional connections. Lastly, the project adopts a continuous feedback approach, integrating insights from students, academics and industry members to ensure relevance and responsiveness to changing demands. As a result, it is hoped that graduates emerge with a strong technical foundation alongside the practical skills and professional acumen needed to thrive in the competitive IT workplace. Once the project process is complete, these potential graduates are required to present their projects at our annual Projects Day to foster engagement and to help prepare students for the workplace.

### 3.2. Projects Day Process

The top 25 teams are selected for our annual event, referred to as Projects Day, where they are required to showcase their work to industry judges. Presenting a project, especially in a competitive or academic setting, is an invaluable experience that offers a multitude of benefits for participants. It's not just about showcasing the end result; it's about the journey of transforming an idea into something tangible and impactful (Razzouk & Shute, 2012). Participating in project presentations is a multifaceted

learning opportunity that enhances teamwork and collaboration skills, boosts confidence through public speaking, offers networking opportunities with industry professionals and peers, and provides valuable constructive feedback for both personal and project growth. Additionally, presenting projects, especially at recognised events, significantly enriches one's resumé or portfolio by showcasing not only subject-matter expertise but also essential soft skills like communication, teamwork, and resilience, thereby opening doors to future opportunities in professional and personal development (Lucas & Spencer, 2018). The full Project Day process is divided into three distinct stages, namely, presentations, judging, networking and feedback.

### *3.2.1. Presentations*

Students are required to present their projects throughout the day to all attendees, which include judges, academic staff, high school learners, primary school learners, and all other attendees. In the context of presenting their projects, students are tasked with presenting their projects by identifying the problem which they are addressing and their corresponding solutions in a clear and engaging manner. This presentation process is not only a critical component of their academic assessment but also serves to prepare them for the dynamics of the workplace. When students present their projects, they typically begin by outlining the specific software problem that they identified. This involves,

- Contextualising the Problem: Students are expected to explain the relevance of the problem within the industry or a specific context, emphasising its impact on users or businesses. For instance, they might detail how a specific software inefficiency affects productivity or user experience.
- Detailing the Research and Analysis: Following the problem statement, students should demonstrate their analytical skills by discussing the research methods which they used to quantify the problem. This might include user feedback, system performance metrics, or existing literature that supports their findings.
- Proposing Solutions: The next crucial step is to present their proposed solutions. Students are encouraged to outline their approach systematically, covering the design, development

process, and any technologies used. They should highlight key features, functionality, and how their solution addresses the identified problem.

- Demonstrating the Solution: Most presentations culminate in a live demonstration of the software. This allows students to showcase their coding skills and the feasibility of their solution. They must handle this portion skilfully, navigating potential questions and technical challenges, much like they would in a real-world setting.
- Receiving Feedback: Finally, the presentation may include a discussion of how feedback can be incorporated into their project for the future. This indicates to judges and attendees that students are open to critique and committed to continuous improvement, a vital trait in the workplace.

The process of presenting software problems and their solutions instils several key soft skills that are essential for success in the IT industry, such as communication skills, critical thinking and problem-solving, collaboration and teamwork, project management and finally, technical proficiency. The presentation process provides a robust platform for IT students to showcase their technical and soft skills, simulating real-world challenges that they will face in their careers. The next stage of this process is the judging from industry leaders.

### *3.2.2. Judging*

For the Projects Day, the Academy of Computer Science and Software Engineering invites expert judges, which include alumni and expert professionals in the IT field. A head judge is assigned to coordinate the judging process; this is undertaken to ensure that the students are judged at an industry level and to prevent any bias that may be introduced by academic staff. The judging criteria used by the judges is the following:

- **Problem Definition:** In the IT sector, identifying a relevant and precise problem is crucial. By focusing on the clarity and significance of the problem being addressed, students learn to analyse real-world issues critically. This skill is essential for future roles, where defining the problem accurately can make the difference between a successful project and a failed one.

- **Solution Design and Innovation:** Encouraging students to think outside the box fosters creative problem-solving. The ability to approach familiar problems from a new angle or to innovate solutions is highly valued in the industry. Evaluating the breadth and depth of the application's impact helps students to understand the importance of scalability and user reach, which are key factors in business success.
- **Technical Architecture and User Experience:** The focus on sound technical architecture equips students with knowledge about building modular and maintainable systems. Understanding how to create extensible solutions (SDKs or APIs) prepares them for collaborative work environments and integration tasks often found in professional settings. Additionally, the emphasis on intuitive user interfaces emphasises the growing importance of user experience in software development, ensuring that students prioritise usability in their work.
- **Business Viability:** Bridging technical projects with business understanding is vital. By evaluating the commercial potential of their solutions, students gain insights into market needs and the feasibility of their ideas. This criterion helps them to appreciate that technical skills must align with business objectives to create successful products.
- **Presentation:** The ability to communicate effectively is indispensable in the tech industry. By requiring compelling presentations that provide context, functionality, and demonstrations, students hone their skills in articulating complex ideas clearly and confidently. This not only prepares them for pitches to stakeholders but also fosters their ability to collaborate in diverse teams.

These criteria not only assess the technical and conceptual rigour of students' projects but also provide invaluable experience in critical thinking, innovation, user-centric design, market understanding, and effective communication, all of which are essential skills for thriving in today's IT industry.

### *3.2.3. Feedback and Networking*

Finally, students are given the opportunity to receive feedback and network throughout the event. The feedback allows students

to engage with industry leaders who are potentially recruiting. This opportunity is invaluable as it gives the student a platform to potentially receive employment once graduated. First and foremost, receiving feedback from industry leaders allows students to understand their strengths and identify areas for improvement. Constructive criticism from experienced professionals can provide valuable insights that classroom learning may not cover, as supported by Mainga *et al.*, (2022). By engaging in real-world discussions, students can gain perspective on the skills in demand, as well as the expectations that potential employers have. This direct interaction with industry leaders and potential recruiters can also help students to refine their resumés and interview techniques based on the feedback received, making them more competitive in the job market.

Networking during the event serves as another significant advantage. Building connections with industry professionals can open doors to internships and job opportunities that may not be advertised. Through networking, students can establish relationships that may lead to mentorship, which can significantly enhance their professional development. Moreover, these connections may provide ongoing support as students transition from academic life to their careers. At the event, we host a number of different exhibitors who also actively engage with the students. The ability to network effectively also helps students to practice soft skills such as communication, negotiation, and relationship-building. By engaging with industry leaders and peers, students can boost their confidence and become more adept at articulating their ideas and experiences.

Ultimately, the combination of receiving feedback and establishing a professional network equips students with the tools that they need to navigate the complexities of the job market. This opportunity not only prepares them for employment upon graduation but also fosters a mindset of continuous improvement and lifelong learning, both of which are essential in today's rapidly evolving work environment.

The Project Day process serves as a vital moment for students to showcase their work, engage with peers, and receive valuable feedback from industry professionals. By presenting

their projects, students not only gain practical experience in public speaking and presentation skills but also learn to articulate their ideas clearly and confidently. This process enhances their problem-solving abilities as they address questions and critiques, fostering a deeper understanding of their subject matter. The networking opportunities provided by Projects Day can lead to potential internships and job placements, allowing students to build meaningful connections within the industry. Overall, Projects Day not only celebrates academic achievement but also bridges the gap between education and real-world application, preparing students for future career success.

It is important to acknowledge that universities are not solely vocational training centres. As scholars have argued, higher education institutions fulfil broader epistemic, developmental, and civic purposes beyond immediate labour market alignment. The framework presented in this chapter does not seek to reduce the University's mission to narrow job preparation. Rather, it aims to integrate intellectual formation, technical competence, and social responsiveness in a manner that strengthens both disciplinary depth and graduates' capacity to act effectively within society. In this way, workplace readiness is positioned not as the primary aim of higher education, but as a natural outcome of a richer, capability-oriented educational experience.

## 4. Conclusion

This chapter examined the urgent need to enhance the readiness of IT graduates for the workplace within the South African context. The literature review revealed several critical gaps that contribute to the inadequacy of current educational frameworks in addressing the practical demands of the industry. Key issues identified include a lack of alignment between academic curricula and industry requirements, insufficient emphasis on experiential learning, and the need for better soft skills training. Our proposed framework aims to address these deficiencies by integrating a competency-based approach that closely aligns educational outcomes with industry expectations. By incorporating practical training opportunities, such as collaborative projects with industry partners, we can ensure that IT students gain

relevant hands-on experience. Additionally, the framework emphasises the development of soft skills that are mandatory for workplace success, including teamwork, communication, and problem-solving abilities.

Furthermore, this framework serves to foster a stronger relationship between academia and industry, encouraging ongoing dialogue and collaboration. By bridging the gaps identified in the literature review, our approach not only prepares graduates to meet current industry demands but also equips them with the skills necessary to adapt to the rapidly evolving technological landscape. In conclusion, the challenges highlighted in the literature emphasise the pressing need for educational reforms in IT training. The proposed framework is a step towards creating more effective educational programmes that not only enhance graduate employability but also contribute meaningfully to the South African economy. As the IT field evolves, it's crucial for educational institutions to remain flexible, ensuring that graduates are well-equipped for current and future digital challenges. This study contributes to the discourse on IT education and encourages further research in this essential field. Future research will be in the form of surveys and graduate interviews to quantify the success of the proposed framework.

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# Chapter 14

# Ethical considerations in AI-mediated postgraduate supervision: Balancing innovation and academic integrity

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## Abstract

The increasing adoption of artificial intelligence (AI) in academic research has reshaped scholarly practices while introducing complex ethical risks, particularly around research integrity and academic misconduct. This study proposes a comprehensive quantitative and empirical framework to model how AI misuse contributes to systemic quality degradation, using retractions as a proxy for integrity breaches. Using longitudinal publication and retraction data from Retraction Watch and Scopus, we construct an AI misuse impact index to track the relationship between research output and integrity risks over time. Time series lag analysis reveals that retraction rates most strongly correlate with prior publication volumes at a one-year lag, indicating the rapid manifestation of AI-driven misconduct. To identify critical intervention points, we apply piecewise linear modelling to detect thresholds where retraction rates accelerate disproportionately relative to publication

growth. A plagiarism tolerance threshold is established, beyond which research quality deteriorates unsustainably. Additionally, we introduce a probabilistic damage model, quantifying the risk of systemic integrity failure as AI adoption expands. Results highlight a pronounced post-2009 rise in AI-related integrity risks, with a sharp inflection in 2023 when misconduct indicators exceeded acceptable tolerance levels, signalling a system-wide ethical crisis. The study further proposes a dynamic, data-driven method for calibrating institutional plagiarism thresholds in alignment with evolving integrity risks and AI adoption patterns. This model enables proactive monitoring and policy adjustments, linking integrity governance directly to empirical risk indicators with implications for postgraduate supervision practices and institutional integrity governance. The findings emphasise the urgent need for adaptive, transparent AI oversight frameworks within academia, ensuring that AI complements rather than undermines the ethical and intellectual foundations of research. Future research should extend this work by integrating discipline-specific AI use patterns and developing real-time academic integrity monitoring systems.

**Keywords:** Academic integrity, AI-Mediated supervision, Ethical considerations, Plagiarism tolerance, Responsible AI Use

## 1. Introduction

The increasing use of artificial intelligence (AI) in postgraduate supervision is reshaping academic mentorship, offering new opportunities to enhance research efficiency and streamline administrative tasks, particularly in guiding students through their complex research journeys (Ali, 2020; Altmäe *et al.,* 2023). AI-driven tools are already transforming various aspects of academic work, such as automating literature reviews, managing administrative duties, and providing personalised, data-driven feedback to students (Kamalov *et al.,* 2023; Ali *et al.,* 2024). These innovations hold significant promise, but their integration into postgraduate supervision (an inherently personalised mentorship process) raises unique challenges. Postgraduate supervision extends beyond knowledge transfer; it fosters the

development of critical research skills, ethical reasoning, and professional growth (elements that AI may struggle to replicate or support effectively (Zawacki-Richter *et al.*, 2019; Mauti, 2025). Despite AI's efficiency, concerns are growing about its impact on traditional mentoring, which emphasises human interaction, ethical guidance, and individualised development, particularly in postgraduate education (Nguyen & Vuong 2024; Zhai *et al.*, 2024).

AI tools offer clear benefits for supporting postgraduate research; however, concerns about their potential to undermine academic integrity, encourage over-reliance on technology, and depersonalise supervision remain underexplored (Crawford *et al.*, 2024; Ahmad *et al.*, 2023). The growing integration of AI into research processes may diminish ethical reasoning and weaken the traditional mentorship bond. Also, the rise in article retractions since the coronavirus disease 2019 (COVID-19) pandemic, coinciding with the emergence of tools like ChatGPT, raises questions about AI's role in academic misconduct (Nguyen & Vuong, 2024; Al-Jahwari & Yousif, 2025). This study aims to investigate the systemic risks to research integrity associated with AI misuse in academic publishing by developing a quantitative framework to model and track integrity degradation over time. Specifically, the study seeks to:

1. Construct a quantitative integrity risk index for AI misuse in research by developing an AI misuse impact index using publication and retraction data, quantifying the relationship between AI-driven research output growth and integrity risks. This index serves as an empirical tool for tracking integrity vulnerabilities as AI adoption expands.
2. Identify critical thresholds and tipping points for systemic misconduct through application of piecewise linear modelling and time series lag analysis to detect points where retraction rates accelerate disproportionately relative to publication growth.
3. Establish empirically grounded plagiarism tolerance thresholds and identify critical tipping points that signal the onset of widespread ethical degradation in academic systems.

4. Model the probabilistic risk of systemic integrity failure by introducing a probabilistic damage model that quantifies the risk of systemic research misconduct under varying AI adoption scenarios. This model captures the dynamic interplay between research output, AI misuse, and retraction patterns, providing a predictive tool for monitoring emerging academic integrity crises.
5. Propose a dynamic integrity governance framework for institutions through development of a data-driven, adaptive framework for institutions to calibrate plagiarism tolerance thresholds and integrity policies in response to evolving AI-related risks. This framework links real-time empirical indicators to institutional policy decisions, enabling proactive interventions to sustain research integrity in AI-augmented academic environments.

While this study examines systemic trends in retractions, it is grounded in the reality that postgraduate supervision is the primary context in which research integrity is first nurtured or neglected. Supervisors guide students in ethical writing, citation, and analytical rigour; lapses in this mentorship can permit AI misuse to pass undetected into submitted manuscripts. Thus, rising retraction rates are not merely a publication-level phenomenon but reflect, in part, supervisory gaps in detecting and curbing AI-related misconduct early in the research process.

This study aims to develop a unified framework to assess and manage the risks of AI misuse in academic research, focusing on its impact on retractions and research integrity. We construct an AI misuse impact index to track shifts in retraction patterns over time, especially post-AI adoption. To explore temporal dynamics, we apply lagged correlation analysis to test whether retractions follow publication spikes with delay, identifying optimal intervention timing. Using piecewise linear regression (Yang *et al.*, 2016), we aim to detect thresholds where retractions accelerate disproportionately relative to output, helping to define critical risk points. We also propose a plagiarism tolerance threshold to signal when misconduct exceeds acceptable limits

and test this concept through simulations comparing capped and uncapped misuse scenarios. The model examines institutional enforcement patterns and adapts tolerance levels dynamically. Finally, we develop a probabilistic model to estimate the likelihood of integrity collapse caused by cumulative AI misuse, integrating damage thresholds and failure probabilities to inform early institutional interventions.

We identify key points in postgraduate supervision where AI use should be regulated, using patterns of academic misconduct predicted by machine learning models. The study evaluates AI's impact on students' research skills, ethics, and development, proposing targeted interventions to mitigate risks. It offers a measurable framework for balancing AI efficiency with ethical oversight and supports policy recommendations such as ethical AI guidelines, adaptive plagiarism thresholds, and real-time integrity monitoring to help universities to maintain academic standards while adopting new technologies.

## 2. Research Methods

This study uses a two-stage methodology based on the Cobb-Douglas production function (Balk, 2024) to analyse how AI, human effort, and institutional resources influence research quality in AI-mediated supervision. First, a general model defines the relationship between inputs and research output. Second, the model is extended to account for variation in AI adoption across individuals and institutions. This approach captures both direct and systemic effects of AI use, allowing for empirical validation and informing policy decisions.

Key Definitions:

- Traditional Plagiarism: Unacknowledged appropriation of another's work.
- AI-Mediated Academic Dishonesty: Presenting AI-generated text or ideas as one's own original scholarship without transparency, critique, or proper attribution.
- Turnitin Similarity Score: A measure of textual overlap, used here as an institutional *declared tolerance threshold*. It is not a direct indicator of plagiarism or AI misuse.

## 2.1. The General Case

We propose a model where research quality ($Q$) depends on study resources ($R$), combined effort ($E$), and AI use ($A$). Resources include infrastructure like library and software, while effort reflects student and supervisor contributions. AI acts as a multiplier, enhancing how $R$ and $E$ affect $Q$. The model assumes diminishing returns, beyond certain thresholds, increasing $R$, $E$, or $A$ yields smaller gains. AI tools improve efficiency, accuracy, and reduce misconduct, helping to optimise research outcomes. To quantify these relationships, we introduce elasticities $\alpha$, $\beta$, and $\gamma$, representing the proportional contributions of resources, effort, and AI to research quality, respectively. Thus, we model the research quality as a function of resources, effort, and the technological factor as follows:

$$Q = A^{\gamma} R^{\alpha} E^{\beta}, \tag{1}$$

such that $\gamma, \alpha, \beta \in [0,1]$, satisfying the condition that $\gamma + \alpha + \beta = 1$ always. The parameters $\gamma, \alpha, \beta \in [0,1]$ represent the elasticities of research quality with respect to AI adoption, resources, and effort, respectively, with $\gamma + \alpha + \beta = 1$ ensuring constant returns to scale. While in a strict economic interpretation these would typically be positive, we allow for the possibility of zero values to model scenarios where a particular input has negligible impact. We also assume that the initial values $A(0), R(0), E(0) \geq 0$. Through this model, we capture the interactions between these variables and can assess how changes in resources, effort, and technological enhancement influence the overall research quality. The condition that $\gamma + \alpha + \beta = 1$ enforces constant returns to scale, meaning that a proportional increase in all inputs results in a proportional increase in research quality. The model assumes that increased resources, effort, and AI use improve research output without excessive inflation. This helps to evaluate how different inputs affect research quality and integrity, guiding supervision policies. The mathematical model employs a Cobb–Douglas production function, a standard framework in economics for modelling multi-input systems. All derivatives, optimisations, and probabilistic extensions have been derived and checked for

internal consistency, dimensional accuracy, and conceptual soundness.

To begin, we assess the impact of AI on research quality by comparing expected and actual research output within our proposed model. By analysing cases where AI leads to increased retraction rates or diminished originality, we can determine appropriate intervention strategies, such as adjusting AI usage policies or modifying academic integrity thresholds. Research quality follows the functional form given in (1) and if AI does not influence research quality, we define the expected research quality in AI's absence ($\gamma = 0$) as:

$$Q^* = R^\alpha E^\beta, \tag{2}$$

where $Q^* \leq Q$ represents the baseline research quality determined solely by resources and effort and $\alpha + \beta = 1$. The difference between actual and expected research quality allows us to isolate the impact of AI:

$$\Delta Q = Q - Q^* = A^\gamma R^\alpha E^\beta - R^\alpha E^\beta, \tag{3}$$

Rearranging, we obtain:

$$\Delta Q = R^\alpha E^\beta (A^\gamma - 1). \tag{4}$$

The model is not mathematically tractable if $A = 1$, hence we consider the case when $A > 1$, then $\Delta Q > 0$, suggesting that AI enhances research output, potentially by improving access to information, automating writing assistance, or refining data analysis. Conversely, if $0 < A < 1$, then $\Delta Q < 0$, implying that AI negatively impacts research quality, possibly caused by overreliance on automated systems, increased plagiarism, or decreased originality in academic work. In Figure 14.1, we demonstrate the nature of the trajectory of $\Delta Q$ when $A > 1$ revealing a monotonically increasing graph confirming that higher AI use tends to correlate with greater deviations in research quality relative to baseline expectations. This framework allows for the empirical measurement of AI's effect on research quality by estimating the deviation of actual output from expected output.

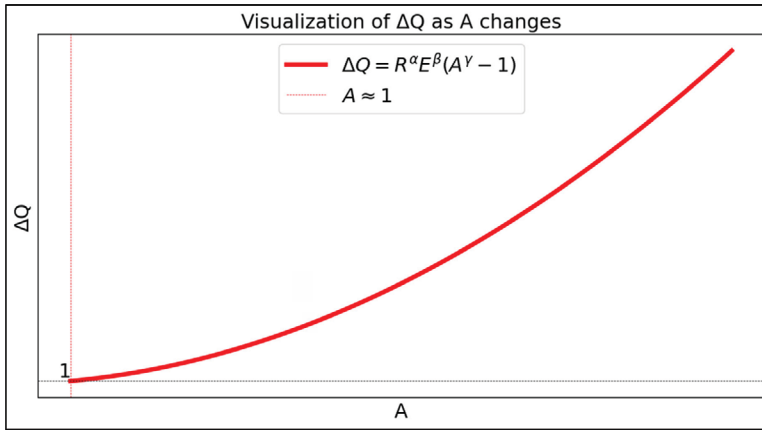



**Figure 14.1:** Graph of $\Delta Q$ as $A$ changes for a constant $\gamma > 0$: The symbolic graph indicates a positive correlation between $A$ and $\Delta Q$, suggesting that higher values of A lead to a greater increase in $\Delta Q$.

We derive the first-order conditions (FOCs) to determine the optimal allocation of AI, resources and effort for maximising research quality. Given the research output function in Equation (1), we take the partial derivatives with respect to $A, R$ and $E$ to analyse how research quality responds to changes in these inputs. The partial derivative with respect to $A$ is

$$\frac{\partial Q}{\partial A} = \gamma A^{\gamma - 1} R^{\alpha} E^{\beta}. \tag{5}$$

Setting this equal to zero would imply an optimal AI level, but because AI usage is typically a decision rather than a resource that can be infinitely adjusted, we must incorporate its cost to make this equation meaningful. We assume that there is a cost associated with AI usage, denoted as $c(A)$ a cost per unit of AI. For simplicity, we assume a linear function $c(A) = kA$. Resources which include expenses related to AI subscriptions, books, databases, computational tools, and AI-driven research assistants have a cost $r$. Investing in more resources incurs higher costs, which must be balanced against their contribution to research quality. We also assume that the cost per unit of effort is $w$, representing the opportunity cost of time and energy expended by students and supervisors in conducting research.

This can be interpreted as workload, time spent on revisions, or even financial costs such as research grants. The optimisation problem now becomes:

$$\max_{A,R,E}[Q - (rR + wE + c(A))]. \tag{6}$$

Taking the first-order condition of Equation (6) with respect to $A$ from (1) and (5), we get that

$$c'(A) = k = \gamma A^{\gamma-1} R^{\alpha} E^{\beta}. \tag{7}$$

This equation states that the marginal benefit of AI on research quality should equal its marginal cost. If AI is costly or leads to unintended negative consequences (such as increased retractions or loss of originality), adjusting its usage becomes necessary. If the marginal benefit of AI exceeds $k$, (that is, $\gamma A^{\gamma-1} R^{\alpha} E^{\beta} > k$), increasing $A$ raises net quality; if below $k$, decreasing $A$ is optimal. If the optimal AI level is exceeded (that is, $A$ is too high), it may indicate that AI is replacing genuine research effort rather than complementing it, necessitating intervention.

For resources, the first-order condition is:

$$\frac{\partial Q}{\partial R} = \alpha A^{\gamma} R^{\alpha-1} E^{\beta}. \tag{8}$$

This result implies that when $\alpha$ is high, resources such as library access, technological tools, and academic databases play a vital role in improving research quality. If $R$ is too low, investing in these resources becomes essential to maintain high research standards. Conversely, when $\alpha$ is low, the impact of additional resources is minimal, indicating that increasing $R$ does not substantially enhance research quality. Instead, other factors such as researcher effort or AI play a more dominant role.

For effort, the first-order condition is:

$$\frac{\partial Q}{\partial E} = \beta A^{\gamma} R^{\alpha} E^{\beta-1}. \tag{9}$$

This result suggests that if $\beta$ is high, research quality is more dependent on human effort. A low level of effort, particularly caused by an over-reliance on AI tools, may compromise academic rigour and originality. To determine the optimal balance between

resources, effort, and AI usage, we introduce a cost function that includes the cost of resources ($rR$) and the cost of effort ($wE$). The objective is to maximise net research quality:

$$\max_{A,R,E}[Q - (rR + wE + c(A))]. \tag{10}$$

Taking the first-order conditions for this optimisation problem, we obtain that:

$$r = \alpha A^{\gamma} R^{\alpha-1} E^{\beta} \text{ and } w = \beta A^{\gamma} R^{\alpha} E^{\beta-1}.$$

These conditions establish equilibrium points where the marginal contribution of resources and effort to research quality equals their respective costs.

We introduce a utility framework that incorporates a temporal adjustment mechanism, recognising that the perceived value of research output evolves over time. As AI becomes more integrated into research practices, its marginal utility diminishes because of factors such as over-reliance, reduced originality, and ethical concerns. We introduce a discounting factor, $\delta \in [0,1]$, which adjusts the utility derived from each additional AI-enhanced research output, where $n(t)$ is the number of published articles on AI. Thus, each AI publication reduces the utility premium of AI by a factor of δ. The students' utility at time $t$ follows:

$$U(t) = U(Q_{\infty}) + \delta^{n(t)}\left[U(Q_0) - U(Q_{\infty})\right]. \tag{11}$$

where $U(Q_0)$ and $U(Q_{\infty})$ represent the utility levels when AI use is minimal and at its maximum saturation, respectively and $Q_{\infty} = \max_{A,R,E}$ $[Q - (rR + wE + c(A))]$ as given in Equation (10). This formulation captures the transition from initial AI adoption, where its benefits are pronounced, to a scenario where excessive reliance leads to diminishing returns. The discounting effect ensures that AI usage is dynamically regulated, preventing overuse that might compromise research integrity. By fitting this model to AI publication data, we obtained the following fitted parameters $\delta = 0.8123, U(Q_0) = 7.26 \times 10^{-16}, U(Q_{\infty}) = 1$ and an $R^2$ value of 0.8735 indicating a solid fit to the observed trends.

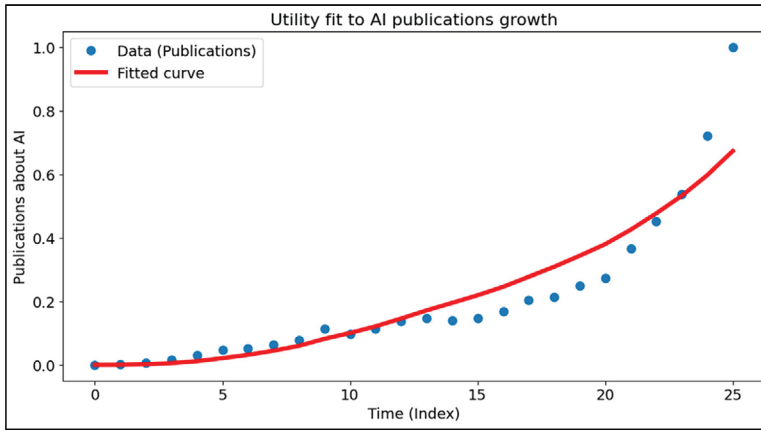



**Figure 14.2:** Fitted utility curve modelling the evolving impact of AI-enhanced research over time with estimated initial values for $\delta$, $U(Q_0)$, $U(Q_\infty)$ being 1, 0 and 0.95 respectively.

The AI publications data is a proxy for AI awareness growth and spread annually. The results in Figure 14.2 suggest that while the initial perceived utility of AI-enhanced research was almost negligible, it increased rapidly with adoption and then gradually levelled off as the number of AI-related publications grew. The long-term utility stabilises at a positive value of 1, which means that even in a saturated research environment, AI maintains a lasting, meaningful contribution. However, its incremental benefits diminish over time, emphasising the importance of thoughtful and measured AI adoption in research to preserve both the value of AI and the integrity of the research field as it continues to evolve. For the rest of the study, without loss of generality, we work with the maximum utility 1, which is negligible as a factor and does not affect the model's outcomes.

## 2.2. The Heterogenous Case

To model the heterogeneity of AI use within postgraduate research with maximum utility, we introduce an AI adoption distribution function that accounts for variations across researchers, disciplines, and institutions. This approach deviates

from the assumption of uniform AI utilisation by acknowledging that AI integration into research workflows is influenced by factors such as familiarity with AI tools, institutional policies, ethical considerations, and field-specific norms. To understand individual student behaviour, we introduce distinct researcher types indexed by $i = 0,..,n$, where each researcher $i$ uses AI at a distinct level $A_i$. The aggregate research quality across all researchers is then expressed as:

$$Q_{agg} = \sum_i A_i^{\gamma} R^{\alpha} E^{\beta}. \tag{12}$$

In cases where AI heterogeneity arises because of institutional access, career incentives, or disciplinary norms, we define AI use for researcher $i$ as $A_i = A_0 + \theta_i A_0$ where $A_0$ represents baseline AI access, and $\theta_i$ captures individual deviations caused by external factors or preferences. If excessive AI use compromises research integrity, institutions may restrict its application in specific areas. Conversely, if underuse results from limited access or insufficient training, policies may prioritise AI literacy and equitable access to resources.

Building on the understanding that AI adoption varies across different research tasks, we model the effect of AI use on research quality by treating research output as a collection of individual research articles within a broader academic research space, denoted as $B$. The articles within the research space $B$ are put into classes $b_1, b_2, \ldots, b_j$, where each $b_j$ corresponds to a specific aspect of research quality, such as novelty, proper citation practices, depth of analysis, and evaluative reasoning. For simplicity, we assume that each $b_j$ is independent of the rest; hence, coupling or cross terms are not considered. To account for AI's influence, we assume a baseline set of AI usage levels $A_0 = \{z_1, z_2, \ldots, z_k\}$ where each $z_i$ represents the responsible, acceptable level of AI use that supports quality research in the corresponding component $b_i$ without undermining academic standards. However, the actual AI use intensities, denoted as $\theta_i A_0 = \{s_1, s_2, \ldots, s_k\}$ can deviate from these baselines, potentially introducing ethical risks to research quality. To quantify the deviation from responsible AI use, we

define the difference between actual AI use and the baseline levels in each $b_j$ as:

$$\{t_{11}, t_{12}, \ldots, t_{kj}\} = \{s_{11}, s_{12}, \ldots, s_{kj}\} - \{z_{11}, z_{12}, \ldots, z_{kj}\}. \quad (13)$$

Each research component $b_j$ exhibits two functions: $\Gamma_j(t_{kj})$, which captures the positive contribution of AI within an acceptable range of use, and $d_j(t_{kj})$, which quantifies the potential negative effects of AI overuse. These negative effects may include issues such as increased plagiarism, reliance on AI-generated content, reduced originality, or weakened engagement with research materials. To prevent AI use from exceeding acceptable thresholds, we introduce a damage limit $\varphi_j$ for each research component $b_j$, enforcing the condition:

$$\sum_{t_{kj} \in T} d_j(t_{kj}) < \varphi_j \text{ for all } k. \quad (14)$$

where $T$ represents the set of AI use deviations beyond the baseline. If the cumulative negative impact $D_j(t)$ for any component exceeds $\varphi_j$, research quality is considered compromised within that dimension. This reasoning is illustrated in the model flow in Figure 14.3.

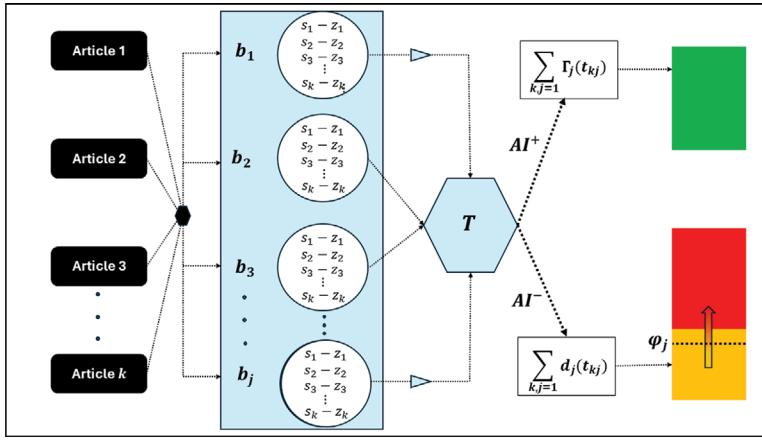



**Figure 14.3:** An illustration of how the model classifies and quantifies positive and negative gains by considering the research components $b_j$. The arrows for $AI^+$ and $AI^-$ denote positive and negative benefits of AI use respectively.

By combining these ideas, we can express the total research quality as a sum overall quality dimension. Specifically, the overall research quality can be written as

$$Q_{agg} = \sum_{k}^{K}\left(\sum_{i=1}^{N}\left(\sum_{i} A_i^{\gamma} R^{\alpha} E^{\beta}\left[\Gamma_j(t_{kj}) - d_j(t_{kj})\right]\right)\right). \tag{15}$$

The inner summation over $i$ aggregates the contributions from all researchers based on their individual AI use $A_i$ (modulated *by* $A_i^{\gamma}$), research rigour $R^{\alpha}$, and student effort $E^{\beta}$. The function $\Gamma_j(t_{kj})$ represents the beneficial contribution of AI to the $k$-th component when operating at its baseline level $z_i$, while $d_j(t_{kj})$ captures the detrimental impact arising from deviations $t_{kj}$ beyond the baseline. The cumulative damage for each research component $b_j$ is calculated based on the deviations $t_{kj}$ and if the total negative impact $d_j(t_{kj})$ for any dimension exceeds its threshold $\varphi_j$, we consider that component to have experienced a compromise in research quality, allowing for the management of AI adoption in research. The plagiarism tolerance $P$ is directly related to the acceptable threshold for negative effects arising from AI use. In this context, we define damage tolerance $\varphi_j$ as the upper limit for damage within each research component $b_j$, and plagiarism tolerance $P$ as the threshold that ensures research quality remains uncompromised. The relationship between damage tolerance and plagiarism tolerance can be expressed as follows:

$$d_j(t_{kj}) \leq \varphi_j \leq P \tag{16}$$

This means that the cumulative damage resulting from AI overuse should not exceed the plagiarism tolerance $P$, which serves as the limit that ensures that the integrity of research is maintained. When introducing plagiarism tolerance $P$ into the overall research quality $Q_{agg}$, we must account for the effect of AI overuse on the research quality. The cumulative damage for each research component $b_j$ influences the research quality, as seen in Equation (15). The role of plagiarism tolerance $P$ is to prevent cumulative damage from exceeding the acceptable limits. This ensures that $d_j(t_{kj})$ does not exceed the threshold at which research quality would be compromised. If $d_j(t_{kj})$ exceeds $P$, strict intervention is required to mitigate the overuse of AI and prevent further damage to research quality (for example, the faculty can

reject a thesis submission). If $d_j(t_{kj}) \leq \varphi_j \leq P$, the research quality remains unaffected by AI overuse, and the total quality $Q_{agg}$ is not compromised. To account for plagiarism tolerance in adjusting the overall research quality $Q_{agg}$, a correction factor is introduced into the formula for total quality. This reflects the impact of the acceptable damage caused by AI overuse:

$$Q_{agg} = \sum_{k}^{K}\left(\sum_{i=1}^{N}\left(\sum_{i} A_i^{\gamma} R^{\alpha} E^{\beta}\left[\Gamma_j(t_{kj}) - min(d_j(t_{kj}), P)\right]\right)\right). \quad (17)$$

The minimum function ensures that if the damage $d_j(t_{kj})$ exceeds $\varphi_j$, the damage is capped at $P$ to prevent further degradation of research quality. If the damage is less than or equal to $\varphi_j$, it remains as is, contributing to the overall quality without requiring intervention. The inclusion of plagiarism tolerance $P$ in the formula for $Q_{agg}$ ensures that AI overuse, particularly regarding plagiarism or reduced originality, does not undermine research quality beyond an acceptable threshold. This threshold is determined by $P$, and intervention occurs when damage exceeds this value, adjusting the total quality to account for the negative impacts of AI. Therefore, $P$ sets the upper limit for the damage $d_j(t_{kj})$ that is acceptable to maintain research quality, and the total research quality $Q_{agg}$is dynamically adjusted to prevent AI overuse from undermining important aspects such as originality, rigour, and academic integrity.

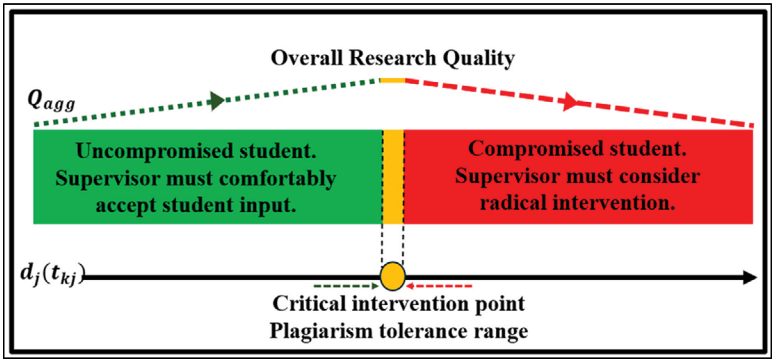



**Figure 14.4:** A schematic illustration of the effect of AI use and abuse. Initially, students are presumed to be responsible and at the end, the damage calls for radical intervention.

Figure 14.4 presents two scenarios: in the case of an uncompromised student ($d_j(t_{kj}) < \varphi_j$), the supervisor can comfortably accept the student's input, which contributes positively to the aggregate research quality ($Q_{agg}$). Conversely, if the student is compromised ($d_j(t_{kj}) > P$), the supervisor may need to consider more drastic measures, as indicated by the red zone, which poses a threat to research quality. The intervention point serves as a critical boundary (when $\varphi_j < d_j(t_{kj}) < P$), prompting the supervisor to decide whether intervention is necessary based on the student's performance within the plagiarism tolerance range. This visual representation reinforces the delicate balance between student autonomy and the need for oversight in ensuring high-quality research output.

## 2.3. Modelling with Data

This study relies on two core datasets as shown in Figure 14.5: the number of peer-reviewed published articles, and the number of retracted articles. Each dataset is selected based on its alignment with the central aim of analysing the relationship between research capacity, research output, and research integrity. The

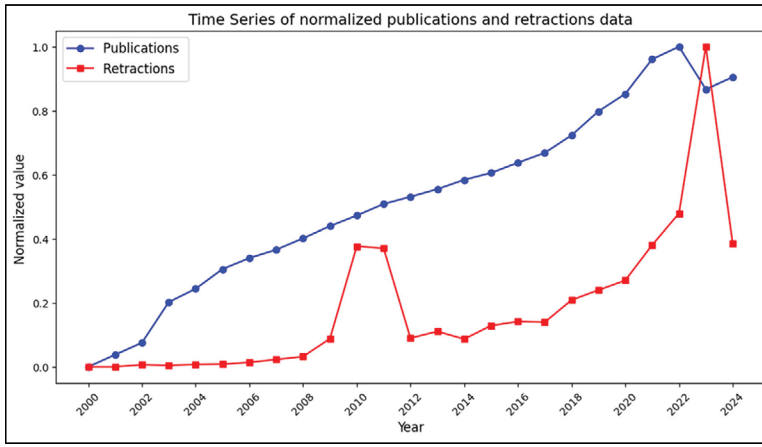



**Figure 14.5:** The plot illustrates the evolving relationship amongst the three variables. A notable rise in retractions is observed after 2011–2012, following earlier increases in publications, suggesting a possible quality–quantity trade-off.

temporal scope of all datasets spans from 2000 to 2024, providing a 24-year window that enables the capture of long-term structural and systemic trends in global scientific production.

The publication and retraction datasets are derived from the Scopus database. Scopus is selected because of its broad disciplinary coverage, standardised indexing practices, and global reach, making it a suitable source for analysing trends in scholarly output across time and regions. Scopus includes metadata on authorship, affiliations, and document types, which supports disaggregation and further analysis. Its reliability and comprehensiveness make it an appropriate proxy for global research activity and integrity.

Retractions are formal notices that a publication has been withdrawn because of error, misconduct, or other violations of publication ethics. While retractions do not capture all dimensions of research integrity, they are one of the few standardised and publicly traceable signals of compromised scientific quality. Including this metric allows the study to empirically assess how the growth of research output may affect the prevalence of integrity failures. The global scope of retraction data is intentional, as research misconduct and correction practices are not limited to a specific country or system, and cross-national trends in retractions are evidence of systemic pressures affecting scientific rigour. We normalise all datasets using min-max scaling ([0,1]) to control systemic factors like population growth and expansion in higher education, ensuring that trends reflect real shifts in research behaviour, not structural changes. This allows proportional comparisons across time, revealing whether retraction trends persist when adjusted for rising publication volumes. Normalisation is essential to accurately assess the link between research output and integrity. The datasets feed into a utility function that models how increased activity may trade off with quality, incorporating time lags to capture delayed effects. This approach ensures methodological rigour and interpretive clarity.

Postgraduate supervisors play a vital role in maintaining research integrity, serving as the first checkpoint for detecting AI misuse before it enters the scholarly record. Supervisory negligence, lack of AI literacy, or permissive attitudes towards AI-generated content can allow misconduct to pass undetected

into submitted manuscripts. This creates a direct pathway from supervision failure to journal retraction. Thus, the retraction trends analysed in this study are not merely publication-level phenomena but reflect, in part, systemic weaknesses in postgraduate mentorship and ethical training. Our model implicitly incorporates supervision quality through the "effort" ($E$) variable, where low supervisory engagement increases the risk of AI misuse proceeding to publication.

## 3. Presentation of Results

We provide a comprehensive analysis of research into integrity risks, including the estimation of retraction-based risks and the identification of key thresholds. Lag analysis highlights critical intervention points, while the quantification of plagiarism tolerance emphasises the impact of AI misuse on academic quality. Additionally, we explore the dynamics of institutional enforcement and model the time-to-failure of research quality under sustained AI-related misconduct.

### 3.1. Estimating Retraction-based Integrity Risks

To indirectly estimate the impact of AI misuse on research integrity, we define an AI misuse impact index, denoted as $AI_x(t)$. This index is based on the assumption that retractions are primarily because of some unethical conduct on the part of the authors, and it is calculated as the ratio of the normalised number of retractions to the normalised number of publications in a given year, with a small positive constant $\epsilon$ (set to 0.001) added to the denominator to avoid division by zero in years with negligible publication output. The formula is expressed as:

$$AI_x(t) = \frac{\text{Number of retractions}}{\text{Number of Publications} + \epsilon} \tag{18}$$

A rising value of $AI_x(t)$ indicates an increasing integrity risk relative to research output, potentially reflecting the growing overuse or misuse of AI tools in academic research. Analysing the data, we observe that the $AI_x(t)$ index remains negligible in the early 2000s, with values such as 0.0878 in 2002 and 0.0230 in 2003. However, a sharp increase appears around 2010, where the index jumps to 0.7973, signalling a substantial rise in integrity

risks. This trend continues, with the index reaching 0.3963 in 2021 and 0.4792 in 2022. Notably, it peaks dramatically at 0.7975 in 2023, suggesting a critical point where AI misuse may have exceeded acceptable thresholds, likely corresponding to the plagiarism tolerance *P* in the model.

This pattern in Figure 14.6 aligns closely with the framework's assumptions that before 2010, AI's influence on academic norms appears minimal, with low integrity risks. Between 2010 and 2020, rising AI adoption coincides with steadily increasing retraction rates relative to publications, indicating growing concerns. From 2020 to 2023, the proxy index spikes rapidly, suggesting significant overuse or unethical reliance on AI tools in the model where integrity risks surpass tolerable limits. The finding that $AI_x(t)$ exceeds 1.0 in 2023 strongly suggests that the cumulative damage from AI misuse likely breached both the damage limit $\phi_j$ and plagiarism tolerance P, necessitating strict intervention to preserve research integrity. This pattern aligns closely with the framework's assumptions that before 2010, AI's influence on academic norms appears minimal, with low integrity risks. Between 2010 and 2020, rising AI adoption coincides with steadily increasing retraction rates relative to publications, indicating growing concerns.

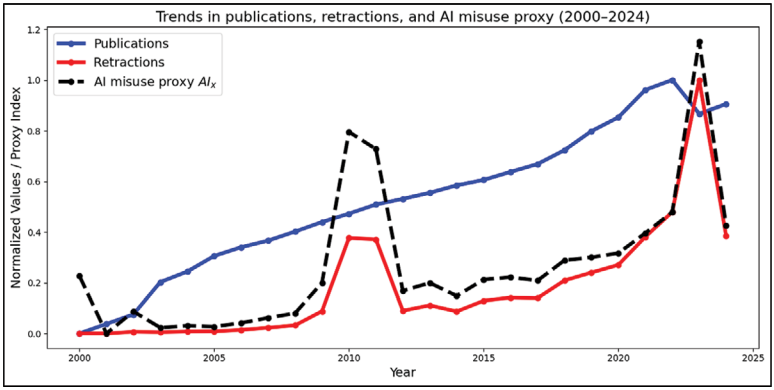



**Figure 14.6:** Normalised trends in publications, retractions, and AI misuse proxy (2000–2024). Notice the sharp AI proxy spikes post-2010 and peaking in 2023, indicating rising integrity risks alongside AI adoption.

### 3.2. Lag Analysis of Retraction Rates and Thresholds Estimation

Using time series correlation and lag analysis, we explore whether spikes in retraction rates follow increases in publication output. The results show that retraction rates are most strongly correlated with submissions one year later (Pearson's correlation coefficient of 0.8576 at lag 1), indicating that unethical AI use, such as plagiarism or manipulation, manifests within a year. As the lag increases, the correlation weakens (0.6207 at lag 2 and 0.4501 at lag 3), supporting the hypothesis that AI-driven misconduct has a relatively short-term impact on retraction decisions.

Given this observation, which is illustrated in Figure 14.7, it is essential to define thresholds for intervention based on the most relevant time window and more specifically, the one-year lag period in which correlations are strongest. We use piecewise linear models rather than nonlinear alternatives like exponential or quadratic functions to identify explicit threshold points where the relationship between normalised publications and retractions changes behaviour. Piecewise linear models estimate these breakpoints directly, making them well-suited for detecting shifts associated with integrity risk thresholds in our theoretical framework. Nonlinear models can capture general trends but do not provide interpretable points of change. The data exhibits distinct phases of growth that align naturally with segmented linear behaviour, supporting the use of this model form.

We apply two models: a two-segment and a three-segment piecewise linear fit. The two-segment model, with an R-squared value of 0.5446, identifies breakpoints at 0.0 and 0.6585 publications, capturing general retraction acceleration. The three-segment model, with a higher R-squared value of 0.7517, identifies breakpoints at 0.0, 0.8525, 0.8615, and 1.0, offering a more detailed analysis. We use the three-segment model, as it provides a more accurate reflection of retraction rate shifts, identifying the P-threshold where retraction rates significantly increase, and interventions may be needed to protect research integrity. In Figure 14.7, the spline reveals whether changes in retraction rates occur abruptly at the breakpoints or follow a continuous, gradual trend, helping to assess if the segmented

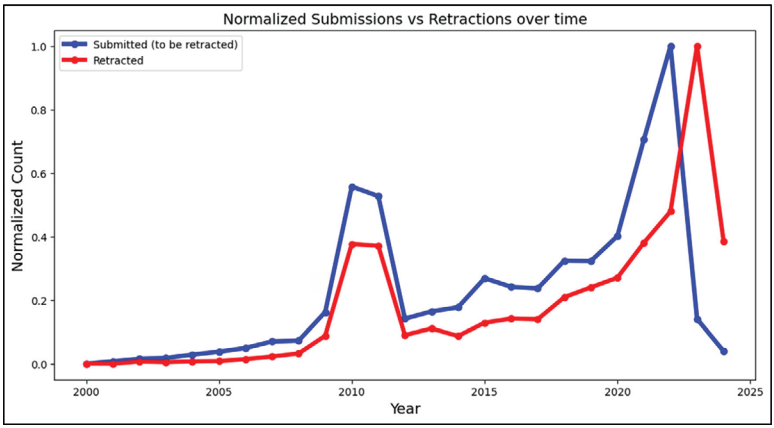



**Figure 14.7:** A comparison of the trends in the number of submissions and retractions from 2000 to 2024.

thresholds reflect real inflection points or oversimplify a nonlinear relationship. These inflections represent key moments when the system's response to publication volume changes, suggesting areas where the retraction rate might either increase or slow down based on trends in AI misuse.

We conduct a piecewise linear analysis to identify thresholds in the relationship between normalised publications and retractions, aiming to pinpoint when retraction rates accelerate (Figure 14.8).

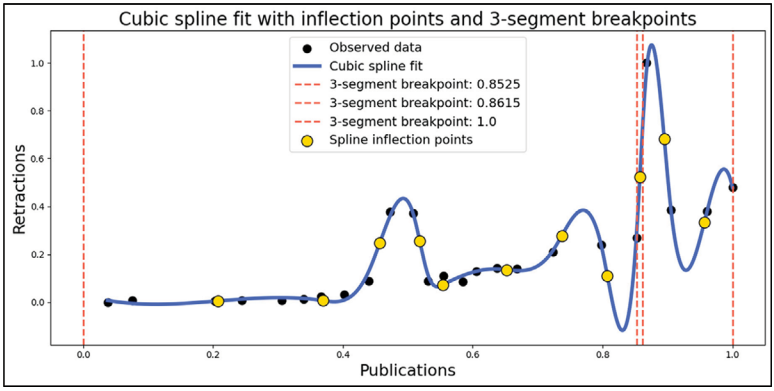



**Figure 14.8:** Comparison of a cubic spline fit to normalised publication and retraction data, overlaid with vertical lines representing the three-segment model breakpoints.

### 3.3. AI-induced Ethical Risks and Plagiarism Tolerance Thresholds

Our model accounts for varying AI adoption across disciplines, institutions, and researchers by introducing individual AI use levels (Equation 12). Using longitudinal data, we calculate a marginal damage ratio, which links retractions to increased scholarly output. We also determine the plagiarism tolerance value by calculating an annual AI misuse impact index, reflecting misconduct relative to academic productivity.

We determine the plagiarism tolerance threshold $P$ by examining the AI misuse impact index, $AI_x(t)$ and identifying the first year in which it exceeds a selected inflection point value derived from the data. This inflection point represents a moment where the relationship between retractions and publication volume begins to shift noticeably, signalling growing systemic risk. The corresponding $AI_x(t)$ value in that year is then set as P. If no year surpasses the selected inflection point, the highest observed $AI_x(t)$ value is used instead. This empirically derived tolerance acts as a cap on AI misuse's damage in subsequent simulations, limiting its degrading effect on overall research quality. Rather than being a theoretical parameter, $P$ is a data-driven indicator of when misconduct begins to accelerate disproportionately relative to academic output, marking a threshold where research integrity is at risk.

To reflect this in the heterogeneous model, we extend the concept of quality to include specific components of research such as originality, citation practices, and rigorous analysis (each represented by subspaces $b_j$). Each of these components has a baseline AI use $z_k$, a beneficial range $\Gamma_j(t_{kj})$ and a damage function $d_j(t_{kj})$, as given in Equation (13). The total quality is adjusted by the minimum of the damage and the threshold $P$, as shown in Equation (15), a formula that operationalises the plagiarism tolerance $P$ as a regulatory boundary. If AI overuse in any dimension $b_j$ causes damage $d_j(t_{kj})$ to exceed $P$, the system triggers intervention to cap further degradation. When damage is within tolerance (see Equation (16)), no correction is needed. This creates a natural "stop" mechanism on the decline of academic

quality, ensuring that research output remains credible even in an AI-augmented environment.

To do this, we calculate the marginal damage from academic retractions relative to the growth in and articles to estimate a plagiarism tolerance threshold $P$. We then simulate overall academic quality $Q_{agg}$ under two scenarios: one where damage is unchecked, and another where it is capped at $P$, to illustrate how enforcing a threshold preserves systemic research integrity. We assign equal weights $\gamma = \alpha = \beta = \frac{1}{3}$ to reflect the assumption that publications and effort equally add to academic quality in the absence of detailed empirical data on their relative impacts. This approach ensures a balanced contribution while maintaining neutrality in the absence of bias towards any one factor. We set $E = 1$ to normalise effort, assuming that it remains constant across years, which is reasonable because academic supervisors with tenure do not have a high turnover rate. This simplification isolates the effects of publications, leaving focus specifically on how damage (via retractions) impacts quality, with and without the plagiarism tolerance threshold.

To derive Figure 14.9, we first compute year-over-year changes in retractions, and published articles, then divide the retraction change by the article change to obtain marginal damage ratio. Using these ratios, we identify the threshold $P$ where damage exceeds a critical value and simulate academic

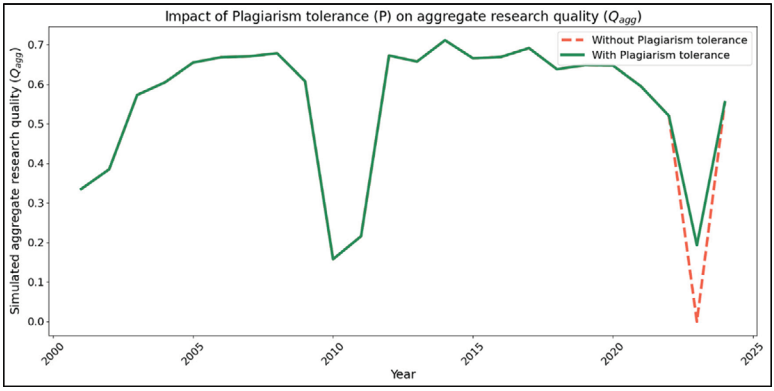



**Figure 14.9:** Simulated academic quality ($Q_{agg}$) with and without plagiarism tolerance.

quality $Q_{agg}$ both with and without capping damage at $P$, showing the impact on system stability through a comparative plot. In the unconstrained scenario, academic quality $Q_{agg}$ erodes rapidly as retractions accelerate past sustainable levels. However, when we enforce the plagiarism tolerance $P$, quality is preserved, and the system stabilises, demonstrating that this threshold has not only mathematical elegance but also real-world utility. A negative aggregate research quality score indicates that AI is being overused to the point where its associated damage (such as plagiarism or loss of originality) outweighs its benefits. This suggests that either the plagiarism tolerance $P$ is too low or the damage function $d_j(t_{kj})$ escalates too rapidly, signalling systemic quality degradation and the need for immediate intervention. The gap between the two curves (green and red) in Figure 14.9 reflects the potential benefit of enforcing a tolerance threshold in controlling the erosion of research integrity

## 3.4. Quantifying Institutional Plagiarism Enforcement

To further contextualise $P$, we map it to familiar academic integrity tools, such as Turnitin, which is simply the acceptable Similarity index at an institution $S$. We begin by considering institutional plagiarism tolerance as a function of both the institution's stated standards and its actual performance in curbing misconduct. The ratio $\frac{AI_x(t)}{S}$ compares the actual impact of AI misuse $AI_x(t)$, which reflects the institution's acceptable plagiarism score, to the declared tolerance threshold ($S$), which is measured by the ratio of retractions to publications. This ratio helps to assess how well an institution's policies align with enforcement. A ratio greater than 1 suggests effective oversight or low misconduct. A ratio near 1 indicates misconduct approaching the declared threshold, requiring stronger oversight. A ratio of less than 1 shows that the retraction rate exceeds the declared tolerance, signalling inadequate enforcement. We introduced earlier the multiplier $P$, which represents the system-wide empirically observed plagiarism tolerance threshold. This threshold is based on the broader trends in AI misuse, where research quality begins to degrade when misconduct rises above

a critical level. By multiplying the ratio $\frac{AI_x(t)}{S}$ by $P$, we scale the institution's tolerance dynamically, aligning it with the system-wide risk of misconduct. This adjustment ensures that institutional thresholds are sensitive to both the institution's own performance and the broader academic environment. Thus, we arrive at the final formula for the adjusted institutional plagiarism tolerance (the ideal one, $S_{ideal}$):

$$S_{ideal} = P \times \frac{AI_x(t)}{S} \tag{19}$$

This formula provides a dynamic and data-driven approach to adjusting an institution's plagiarism tolerance based on both its own conduct and broader systemic trends in academic misconduct. The ratio between the actual retraction rate and the institution's acceptable plagiarism tolerance $\frac{AI_x(t)}{S}$, serves as a diagnostic indicator of policy enforcement and research integrity management. This metric captures the gap between declared academic standards and real-world accountability. For example, if an institution claims an acceptable plagiarism threshold of 20% while the actual retraction rate is 0.1% (equivalent to 1 retraction per 1,000 publications), the resulting ratio would be 0.005. Such a value suggests that the institution's retraction rate is only 0.5% of its stated institution's plagiarism score ($S = 20\%$), suggesting either weak enforcement, low actual misconduct, or underreporting. When the ratio exceeds 1, it signals that misconduct is rising beyond what the institution claims to tolerate, indicating a critical gap between policy and practice that demands immediate attention.

It is important to note that Turnitin and similar tools detect textual similarity, not AI generation or intellectual dishonesty directly. Thus, an institution's declared threshold $S$ may not align with actual integrity risks posed by AI. Our adjusted tolerance $S_{\text{ideal}}$, therefore, serves as a corrective mechanism, scaling declared policies considering empirical misconduct data ($AI_x(t)$) and systemic risk ($Prob(C_t > P)$).

## 3.5. A Probabilistic Integrity Decay Framework

Our model extends to incorporate temporal dynamics that capture how research quality degrades progressively because of sustained

AI misuse. For each research quality dimension $b_1, b_2, \ldots, b_j$, deviations from the ideal AI baseline $z_{kj}$ (quantified as $t_{kj} = s_{kj} - z_{kj}$) introduce incremental damage. These deviations, as defined in Equation (19), manifest as erosion in originality, increased plagiarism, or weakened analytical depth. The cumulative damage to dimension $b_j$ over $t$ years,

$$D_k(t) = \sum_{t_j \in T} d_j(t_{kj}) < \varphi_j, \tag{20}$$

triggers a need for intervention in that dimension if it surpasses the threshold $\varphi_k$. At the system level, total accumulated damage

$$C_t = \sum_{k=1}^{K} D_k(t) \tag{21}$$

is measured against a plagiarism tolerance threshold $P$. System failure occurs when $C_t > P$, with time to intervention marking the earliest point at which corrective actions (consider as examples policy reforms or audits) become necessary. This framework dynamically links AI misuse to quality decay, enabling real-time monitoring of integrity breaches. For damage accumulation, we assume each article's contribution

$$D_i - D_{i-1} = S_i \psi(D_{i-1}), \tag{22}$$

where $S_i$ is the $i$-th article's vulnerability and $\psi(D_{i-1})$ models ethics decay from prior damage. With $\psi(D) = \omega D$ (assume linear decay for simplicity), solving $\sum_{i=1}^{k} S_i$ yields:

$$\ln\left(\frac{D_k}{D_0}\right) \sim \mathcal{N}(\mu_A, \sigma_A^2), \tag{23}$$

revealing log-normally distributed damage. This shows that minor, initially imperceptible deviations compound exponentially, culminating into abrupt ethics failure once $C_t > P$. Consequently, the time to intervention becomes a probabilistic metric, emphasising that integrity breaches often emerge nonlinearly, necessitating proactive monitoring long before thresholds are visibly exceeded.

The risk of failure (when $C_t > P$) can now be probabilistically modeled using the cumulative damage distribution:

$$\text{Prob}(C_t > P) = 1 - \Phi\left(\frac{In\left(\frac{P}{C_0}\right) - \mu_A}{\sigma_A}\right) \tag{24}$$

This equation allows us to quantify the probability of exceeding the threshold based on the AI adoption behaviour. In this expression, $\Phi(\cdot)$ represents the cumulative distribution function (CDF) of the standard normal distribution. The term $C$ stands for the initial level of damage, which we can normalise to 1 for simplicity. The parameters $\mu_A$ and $\sigma_A$ capture the mean and dispersion of AI usage and misuse across researchers, as specified in the AI adoption model. This formulation allows us to probabilistically estimate the risk of breaching the system-wide tolerance threshold based on observed trends in AI misuse and damage accumulation. Hence, we modify Equation (19) to include the probability of exceeding the critical plagiarism tolerance in Equation (24) and get:

$$S_{ideal} = P \times \text{Prob}(C_t > P) \times \frac{AI_X(t)}{S} \tag{25}$$

This adjustment makes $S_{ideal}$ responsive to the probabilistic risk of exceeding the critical plagiarism threshold, scaling tolerance based on both AI adoption and integrity risk. It ensures dynamic regulation, tightening controls as $\text{Prob}(C_t > P)$ rises.

## 4. Discussion of Findings

Integrating AI in postgraduate supervision boosts research efficiency but introduces costs, supervision time, and academic integrity risks. The optimisation framework (Equation 6) balances AI use, resources, and human effort to maximise quality while minimising costs. It guides decisions on when to use AI or rely on mentorship, ensuring that AI enhances quality without compromising ethics. This framework supports responsible AI integration, safeguarding both academic standards and mentorship.

The plagiarism tolerance threshold $P$ = 0.797, with the threshold year being 2009-10, serves as a data-driven intervention point, marking where retractions begin to rise

disproportionately relative to scholarly output. This value, empirically derived from the relationship between academic retractions and output, highlights a critical inflection point where misconduct threatens systemic integrity. Rising retractions, especially when reinforced by lagged effects, suggest the need to lower P to prevent broader ethical failures. A predictive model using lagged retraction data can forecast when this threshold will be exceeded, signalling the need for corrective action. By integrating this threshold into governance practices, institutions can proactively manage academic risk, maintaining research credibility in the face of evolving AI-driven challenges.

The model's accommodation of heterogeneous AI adoption across disciplines (for the same institution, different students' behaviour) represents another important advancement. By incorporating individual-specific AI use levels (as expressed in Equation (12)), the framework recognises that AI's effects are context-dependent. This allows for more tailored policy interventions rather than relying on uniform, oversimplified assumptions. Complementing this is the dynamic damage capping mechanism, wherein $P$ is enforced as a regulatory boundary (Equation (16)), functioning as a circuit breaker that prevents unchecked degradation of research quality. This feature, illustrated in Figure 14.3, demonstrates how capping damage at the empirically derived threshold stabilises aggregate research quality ($Q_{agg}$), offering institutions a pragmatic safeguard.

The marginal damage ratio quantifies the cost of AI misuse per unit of academic productivity, linking retractions to publication growth. This framework incorporates probabilistic risk assessment, modelling integrity breaches as log-normally distributed events via Equations (23) and (24). Because of delays in detection and retraction processes, current retraction rates may underestimate misconduct, particularly in fields adopting AI. This emphasises the importance of the plagiarism tolerance threshold $P$ as an early warning indicator of rising systemic risks before retractions accumulate.

In this integrated model, the log-normal distribution emerges as the natural fit for capturing the accumulated damage caused by the heterogeneity in AI adoption, where the system's

overall quality degradation reflects the skewed distribution of AI reliance. This way, both individual and collective damages from AI use are modelled, with interventions triggered once cumulative damage $C_t$ surpasses a threshold $P$, marking system failure. This log-normal behaviour of cumulative damage implies that while most research systems may remain below the plagiarism tolerance threshold $P$ for an extended period, a smaller subset (caused by compounding misuse and prior degradation) can experience a rapid, disproportionate escalation in damage. As a result, the system-wide risk of crossing the threshold $P$ is not gradual but can manifest suddenly and unexpectedly. This emphasises the importance of early monitoring and intervention, because once the cumulative damage $C_t$ enters the long tail of the log-normal distribution, the probability of surpassing $P$ increases non-linearly, making recovery more difficult and requiring more severe corrective action.

The escalating retraction rates documented in our analysis are not inevitable outcomes of AI adoption but represent failures at specific intervention points. Figure 14.10 maps these points within the research lifecycle, identifying supervision as the most effective stage for integrity preservation. While our data quantifies the systemic damage from unchecked AI misuse, this flow diagram illustrates where and when interventions can most effectively mitigate that damage, offering institutions a visual guide for targeted policy development.

Despite these strengths, the model also presents critical limitations and challenges. One issue lies in the assumption of constant academic effort ($E = 1$), which normalises researcher input and ignores changing trends such as productivity inflation, burnout, or shifts in time allocation driven by AI tools. A more realistic approach would model effort as a function of AI adoption, capturing possible declines in human scholarly contribution. Another limitation is the uniform weighting of quality components ($\gamma = \alpha = \beta = \frac{1}{3}$) in the simulations, which, while practical, may not empirically reflect the relative importance of publications, citations, and effort across different fields. Field-specific weighting schemes, informed by expert surveys or citation network analyses, could address this imbalance.

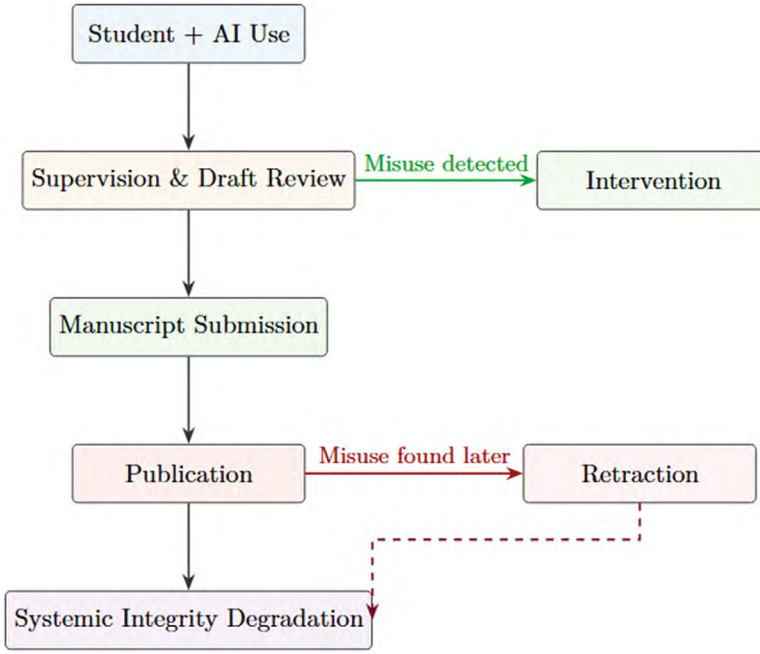



**Figure 14.10:** Conceptual model tracing AI-mediated misconduct through postgraduate research stages. Green pathway: early intervention during supervision prevents escalation. Red pathway: late detection leads to retraction and systemic damage. Supervision serves as the critical intervention point for maintaining research integrity.

The model's reliance on retraction data as a proxy for misconduct also poses challenges, as retractions are noisy indicators and many cases remain unreported, particularly in institutions with weak oversight. To improve robustness, alternative metrics such as post-publication peer review flags and preprint controversies can be incorporated in future work. Furthermore, the assumption of linear ethics decay ($\psi(D) = \omega D$) likely underestimates the risk of cascading failures, where trust in a journal or institution collapses suddenly. Nonlinear decay functions, such as sigmoidal or piecewise models, could better capture these tipping points. Finally, the conceptual subspaces representing originality, citation rigour, and other dimensions ($b_j$) lack operational definitions. These could be grounded in existing bibliometric

indices, such as the OpenCitations Index of Crossref open DOI-to-DOI citations (COCI) for citation rigour or textual reuse detection for originality, to ensure empirical clarity. The framework offers valuable practical implications and directions for refinement. One application is institutional benchmarking, where the ratio $\frac{AI_x(t)}{S}$ could serve as a public accountability metric, revealing gaps between declared policy tolerance and actual retraction rates. Institutions with disproportionately high ratios might undergo audits to align policy with practice. Early warning systems could also be developed by integrating the model with institutional data pipelines, such as plagiarism detection software and internal review reports, to flag departments where the probability of crossing the plagiarism tolerance threshold ($P$) exceeds safe levels. A dashboard visualising trends in academic damage metrics ($D_k(t)$) would help to prioritise interventions.

Our model acknowledges as a weakness, that publishing norms vary by discipline. In Science, Technology, Engineering and Mathematics (STEM) fields, Doctoral candidates are often expected to publish during their studies, which may increase exposure to AI misuse and retraction risk early in their careers. In contrast, in many Humanities and Social Sciences disciplines, the focus remains on the monograph or thesis, with publishing occurring post-graduation. This difference influences when and how AI misuse manifests in the publication record. Nonetheless, the ethical imperative for supervisors to cultivate original, rigorous scholarship remains universal, and our framework's damage thresholds are applicable across research contexts.

## 5. Conclusions and Recommendations

This study explored the ethical implications and academic integrity risks associated with AI-mediated postgraduate supervision. Through a combination of theoretical modelling and empirical data analysis, several notable patterns have emerged. Firstly, while AI significantly enhances research efficiency and accessibility, its overuse introduces risks such as diminished originality, increased retraction rates, and compromised mentorship quality. The study confirms that the relationship between AI integration and research quality is non-linear and

governed by diminishing marginal returns, emphasising the importance of balanced usage.

To preserve the integrity of postgraduate supervision in the era of AI, the following recommendations are proposed:

1. Institutions should develop frameworks on the ethical use of AI that create discipline-sensitive guidelines for AI use in academic work and review them regularly (Papagiannidis *et al.*, 2025).
2. Institutions must enforce plagiarism tolerance thresholds by implementing a dynamic monitoring system that tracks misconduct indicators, such as retraction rates, and triggers proactive intervention.
3. It is essential to integrate AI literacy into research training for both students and supervisors, focusing on ethical AI use and academic writing to prevent overreliance on AI.
4. AI should complement, not replace, mentorship, and institutions should promote human-centred supervision by focusing on interpersonal relationships and ethical guidance (Koeszegi, 2024).
5. Institutions must ensure equitable access to AI resources, guaranteeing fair distribution of tools and training to prevent inequalities in research quality.
6. Finally, institutions should monitor AI's impact on research quality by implementing systems that track AI's influence and ensure it supports critical thinking (Wits Centre for Learning Teaching and Development, 2024).

In conclusion, while AI presents powerful opportunities for enhancing postgraduate research supervision, a comprehensive, data-driven, and ethically conscious approach is essential. The integration of AI must be managed with vigilant oversight, equitable access, and a steadfast commitment to upholding academic integrity and mentorship quality. The findings call for enhanced supervisor training in AI ethics and proactive institutional policies that link supervision quality to long-term research integrity.

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