

MSOR Connections

Articles, case studies and opinion pieces relating to innovative learning, teaching, assessment and support in Mathematics, Statistics and Operational Research in higher education.

Volume 24 No. 1.



Contents

EDITORIAL	3 – 4
– Claire Ketnor and Tony Mann	
RESEARCH ARTICLE: Designing the Student Learning Journey: A Practical Approach to Integrating Generative AI within Higher Education	5 – 32
– Michael Grove	
RESEARCH ARTICLE: The effect of Advanced Higher Mathematics on success within STEM degree-programs	33 – 43
– Nathan Burns, David Young, and Louise Kelly	
RESEARCH ARTICLE: Student Perceptions of TabletPC Use in Mathematics Teaching, and Student Preferences of Different Delivery Modes	45 – 55
Alena Haddley and Joel A. Haddley	
OPINION: Revisiting John Snow's Cholera Map: A Data Visualisation Case Study for Statistical Education	57 – 74
– Niamh Mímnagh	
OPINION: Breaking free: motivating mathematics through escape rooms	75 – 83
– Thomas E. Woolley	
CASE STUDY: Implementing Active Learning in Undergraduate Mathematics Using Tarsia Puzzles	85 – 93
Francis Duah and Boza Tasic	
WORKSHOP REPORT: Diversity and Decolonisation in Mathematics	95 – 101
– Siri Chongchitnan, Ryan L. Acosta Babb, Jonathan Skipp, Helena Verrill, and Elliot M. R. Vincent	
WORKSHOP REPORT: Transformative Workshops Empowering International Postgraduate Students	103–107
– B.K. Ashley Hoolash and Sweta Rout-Hoolash	
WORKSHOP REPORT: FYiMaths (First Year in Mathematics) New South Wales 2024 Meeting Report	109–115
– Amanda J. Shaker, Merryn Horrocks, Deborah King, and Don Shearman	

For information about how to submit an article, notifications of new issues and further information relating to *MSOR Connections*, please visit <https://journals.gre.ac.uk/index.php/msor>.

Editors

Anthony Cronin, University College
Dublin, Ireland
Claire Ketnor, Kaplan Open Learning, UK
Tony Mann, University of Greenwich, UK
Alun Owen, Coventry University, UK
Susan Pawley, The Open University, UK

Editorial Board

Noel-Ann Bradshaw, University of Greenwich, UK;
Cosette Crisan, University College London, UK;
Francis Duah, University of Chichester, UK;
Jonathan Gillard, Cardiff University, UK;
Duncan Lawson, Coventry University, UK;
Michael Liebendörfer, Paderborn University,
Germany;
Birgit Loch, La Trobe University, Australia;
Ciarán Mac an Bhaird, Maynooth University,
Ireland;
Eabhnat Ni Fhloinn, Dublin City University,
Ireland;
Matina Rassias, University College London, UK;
Josef Rebenda, Brno University of Technology,
Czech Republic;
Frode Rønning, Norwegian University of Science
and Technology, Norway;
Katherine Seaton, La Trobe University, Australia.

This journal is published with the support of the **sigma** network and the University of Greenwich Faculty of Engineering and Science.



Editorial

Claire Ketnor, Kaplan Open Learning, UK

Tony Mann, School of Computing and Mathematical Sciences, University of Greenwich, UK

Email: a.mann@gre.ac.uk

Welcome to the first issue of Volume 24 of *MSOR Connections*. This issue contains a generous mix of articles. A theme throughout the papers is student success, whether that be prior to university, during university or subsequently within careers. The authors of the papers have taken different approaches, which includes both the use of physical resources (escape rooms and Tarsia puzzles) and the incorporation of technology (such as AI and statistical software).

We lead with an analysis of the use of generative AI in mathematics higher education by Grove. Although this article exceeds our usual word-length expectations, we have decided to publish it in full because of the importance of the topic. The author's position and experience mean that this important paper is an exceptionally valuable contribution to the current discussion of the topic, which is particularly current within higher education at the moment. The paper contains many useful points to consider, such as programme-level planning, and asks lots of fundamental questions. Truly embracing AI, the author presents a range of useful examples that readers can take inspiration from.

The transition to higher education is a topic of importance to many of our readers, and the paper by Burns, Young and Kelly provides analysis of the Scottish Advanced Higher Mathematics qualification and its value for those who progress STEM subjects in higher education. The authors explore important questions and highlight how students may be less likely to succeed on some courses without the advanced qualification in Mathematics.

Haddley and Haddley, in their paper, challenge the use of traditional teaching approaches, discuss the use of tablet PCs in mathematics teaching, and present student preferences for modes of teaching, recommending that educators "consider the value of different tools and their individual advantages when planning teaching activities, rather than being led by a strong discipline culture".

The use of data is increasingly a vital component of mathematics graduate careers. Mimmagh shows how the pioneering work of John Snow in the middle of the nineteenth century can be used in the training of statisticians in the twenty-first century. Mimmagh creates a powerful educational experience by using technology to give visual clues to enable students to undertake real-world problem solving, building upon the motivating historical example by making links with modern topics.

The paper by Mimmagh isn't the only paper to contain a historical example. Wooley uses Bletchley Park as the context of an escape room by utilising physical resources instead of digital ones. Duah and Tasic also present innovative ways to engage and motivate students using paper-based Tarsia puzzles.

The issue concludes with three workshop reports by Chongchitnan et al, Hoolash and Rout-Hoolash, and Shaker et al. As presented by Chongchitnan et al, many initiatives and challenges were explored within the diversity and decolonisation workshop, and there is demand for more work in this area. Hoolash and Rout-Hoolash present information on a number of workshops for international students, which were created by careful consideration of the student group and the circumstances. Shaker et al present details of their workshop that contained a variety of topics, many of which also feature in other papers in this edition. This includes active learning, AI, outreach, preparedness, statistics visualisation and real-world problem solving.

We hope that you will find much to interest you in this issue.

MSOR Connections can only function if the community it serves continues to provide content, so we strongly encourage you to consider writing research articles or case studies about your practice, accounts of your research into teaching, learning, assessment and support, and your opinions on issues you face in your work.

Another important way readers can help with the functioning of the journal is by volunteering as peer reviewers. When you register with the journal website, there is an option to tick to register as a reviewer. It is very helpful if you provide appropriate information in the 'reviewing interests' box, so that when we are selecting reviewers for a paper we can know what sorts of articles you feel comfortable reviewing. To submit an article or register as a reviewer, just go to <http://journals.gre.ac.uk/> and look for *MSOR Connections*.

RESEARCH ARTICLE

Designing the Student Learning Journey: A Practical Approach to Integrating Generative AI within Higher Education

Michael Grove, School of Mathematics, The University of Birmingham, Birmingham, UK.

Email: m.j.grove@bham.ac.uk

Abstract

Generative AI technologies are reshaping higher education, transforming how students access knowledge, engage with learning, and complete assignments. While institutional responses have largely focused on academic integrity and assessment security, this paper argues for a proactive, programme-level approach that embeds generative AI thoughtfully and ethically across the student learning journey. Drawing on examples from the mathematical sciences, it presents a practical framework to support curriculum teams in aligning AI use with programme outcomes, disciplinary values, and assessment design. Key recommendations include designing progression from foundational to advanced AI-supported tasks; fostering coherent, programme-wide expectations for ethical and transparent AI use; and developing students' critical AI literacy as a core graduate attribute. The paper also highlights the importance of equitable access to tools, respecting disciplinary contexts, and rethinking assessment formats to promote higher-order thinking. A programme-level checklist is provided to guide planning and implementation. By integrating generative AI with intentionality, institutions can move beyond reactive policies towards learning environments that prepare students for a future in which human and AI capabilities will increasingly work in partnership.

Keywords: Generative AI, Programme design, Educational policy, Assessment and learning, Responsible integration.

1. Introduction

To date, much of the discourse surrounding generative artificial intelligence (generative AI) in higher education has centred on its implications for assessment: how to detect it, how to mitigate risks, and how to ensure academic integrity. While these are important concerns, a singular focus on assessment risks overlooking the wide, and arguably more transformative, potential of generative AI technologies to support and enhance student learning. These tools, now widely accessible, offer students new ways to explore ideas, test understanding, and personalise their learning experience. Importantly, the ability to use generative AI tools effectively, ethically, and critically will become an increasingly vital graduate attribute.

It would be a mistake to begin by assuming that all students will use generative AI inappropriately or with the intention of gaining unfair advantage. Many are now entering higher education having already experimented with such tools in school or college (Freeman, 2025). They will continue to use these tools to make sense of complex material, generate examples, or check their understanding, especially when they are unsure where else to turn, when support is not available at convenient times, or when it doesn't align with their preferred learning approach. The appeal is clear. Generative AI tools offer what many students perceive as effortless content creation, immediate answers to difficult questions, and personalised feedback on demand. They can generate multiple versions of a written task, suggest how to improve grammar and structure, or provide near-instantaneous solutions to mathematical problems. For students facing uncertainty, time pressure, or confidence barriers, generative AI promises speed, clarity, and convenience.

Generative AI tools also offer a form of personalised learning, tailored prompts, interactive dialogue, practice problems, and 24/7 availability, making them feel more accessible than many traditional forms of academic support. Students use them to summarise lecture content, develop research questions, translate texts, or refine presentation materials. For some, they are a creative partner, for others, a non-judgemental tutor. It is this broad appeal, and their growing role in everyday student study patterns, that makes it essential to engage with generative AI thoughtfully and proactively within programme design.

As educators, we therefore have a responsibility not to ignore or restrict these tools entirely, but to help students learn how to use them well. This includes ensuring that all students:

- Understand the significance of generative AI for their studies and their future careers.
- Recognise appropriate and inappropriate uses of generative AI in the context of learning and assessment.
- Appreciate both the strengths and limitations of generative AI tools as part of their educational experience.
- Develop the skills to ethically and critically use generative AI to support learning and appraise their own progress and understanding.

Student support in this area must be scaffolded. All students should be introduced to these tools through a clear and coherent programme of regular guidance and practical activity. But beyond that, they need opportunities to use generative AI within their discipline, with clear expectations and feedback on the appropriateness and success of their use. When used effectively, these tools can also benefit educators by enhancing their teaching practices, whether through generating practice questions, drafting explanations, developing feedback, or supporting differentiated instruction.

Yet to realise these benefits, the use of generative AI must be designed, and designed with intent. This means asking very fundamental questions about teaching and student learning:

- What do we want students to learn, and why?
- How can we design learning experiences that promote deep, connected, and sustained understanding?
- How might generative AI support the development of disciplinary thinking, academic skills, and graduate attributes?

These are not new questions, but the presence of generative AI in the current learning landscape changes how we must approach them. Consideration of its use can no longer sit outside of learning design, it must now be embedded within it, just as we routinely consider how assessment aligns with learning outcomes. This does not mean every module must require or support the use generative AI tools, nor that their use is always appropriate. In some cases, allowing students to rely on generative AI may risk undermining the very skills and attributes we are seeking to develop, such as constructing arguments, performing symbolic manipulation, or engaging in sustained problem solving. Decisions by educators about when to use, or not use, generative AI must be intentional and transparent.

While some institutions have looked to mitigate misuse through detection tools, these are often unreliable (Weber-Wulff et al., 2023) and risk fostering a climate of mistrust. A more productive approach lies in intentional curriculum design, clear communication, and proactive support for ethical

use of these tools by staff and students. This also underscores the importance of developing staff confidence and capability. Designing for AI-enhanced learning is not solely a technical matter, it also requires academic judgement, disciplinary literacy, and pedagogic intent.

What matters most is coherence. At programme level, students should experience a consistent and well-communicated approach. Where generative AI is encouraged, the rationale should be clear. Where it is limited or restricted, the pedagogical reasons should be explained. Inconsistent messaging, or indeed a lack of communication, only leads to confusion, inequity, or misuse.

This paper explores how programme teams can take a structured and practical approach to integrating generative AI into learning and teaching design. It outlines key design considerations, offers examples of effective practice within the mathematical sciences, and sets out a framework to support students in engaging with these tools confidently and responsibly. The focus is not on replacing teaching or outsourcing thinking, but on how generative AI tools might help us design better learning, preparing students not only for success in higher education, but for the demands of an ever-evolving world of work.

2. Considerations for Design

The integration of generative AI within learning and teaching should not begin with tools or technology, but with the principles of learning design. Specifically, it should be grounded in programme-level learning outcomes (PLOs) and the overarching aims of the curriculum. The following sections outline five key considerations for effective and sustainable integration of generative AI.

Programme-level approaches to integrating generative AI must not only be pedagogically grounded but also aligned with institutional frameworks and guidance. Institutional frameworks provide a shared foundation for practice, ensuring that individual programmes support consistent messaging on academic integrity, ethical use, digital skills, and student support. Aligning with these policies helps ensure students encounter a coherent experience, where the expectations around AI use are both transparent and justifiable across modules and departments. This is particularly important for joint honours or interdisciplinary students, who may otherwise face conflicting guidance across subjects, undermining both equity and clarity.

2.1. Purpose and Progression

Effective design begins by considering the purpose of integrating generative AI and how its use will support student progression across the programme. Programme-level learning outcomes should guide what is taught at the module level, the skills students are expected to develop, and how those skills are assessed. While generative AI may not feature explicitly within these outcomes, many programmes already include references to digital literacy, independent learning, critical thinking, or effective communication. These provide natural points of alignment.

More broadly, generative AI can support the development of higher-level academic skills such as synthesising ideas, identifying relevant knowledge, evaluating information, and applying concepts to unfamiliar contexts. These align closely with the upper levels of Bloom's revised taxonomy: analysing, evaluating, and creating (Anderson & Krathwohl, 2001). A central goal of higher education is to help students move beyond content reproduction and towards critical engagement and original thought. Used well, generative AI can support this progression by acting as a scaffold for inquiry, reflection, and experimentation.

However, the value of generative AI is not limited to these higher levels. In the earlier stages of a programme, students may use AI tools to support foundational cognitive processes, particularly remembering and understanding. For example, they might generate summaries of lecture content or readings, ask for simplified explanations of unfamiliar concepts, build personalised glossaries or revision cards, or translate technical terms into everyday language to check their understanding. These uses can be especially valuable for students who are new to a subject, returning to study, or lacking confidence in academic language or disciplinary conventions. By supporting the consolidation of foundational knowledge, generative AI can help students begin from a more equitable starting point and build their confidence to engage with more complex ideas. As students progress, they may also begin to use generative AI at the applying level, for instance, by creating practice problems or worked examples, exploring variations on standard methods, or testing their ability to adapt a known process to new conditions. These uses allow for greater personalisation and encourage active engagement with content, particularly when students are encouraged to evaluate the relevance and accuracy of what AI tools generate.

In this way, generative AI tools can be embedded across all stages of Bloom's taxonomy (Table 1), supporting student learning in different ways depending on their current level of understanding, the learning outcomes being targeted, and the nature of the discipline. What matters is that the use of generative AI is intentional and clearly aligned with the purpose of the learning activity. By final year, the emphasis should shift towards using generative AI critically and selectively, as one tool amongst perhaps many, to support independent research, synthesis of complex ideas, and the development of original outputs. This progression, from supported use for understanding, to critical use for knowledge creation, should be reflected in programme-level planning and curriculum mapping.

2.2. Designing the Learning Environment

The increasing presence of generative AI in students' academic routines brings with it not only new tools, but also new behaviours. As students learn to engage with AI to ask questions, summarise material, or test understanding, there is a real risk that learning becomes more solitary, transactional, or disconnected. Left unchecked, this shift could undermine core features of a strong university experience such as peer collaboration, dialogue, feedback, and community. Designing effectively for generative AI therefore also means designing around it: identifying what matters in a rich, supportive, and developmental learning environment, and ensuring those features are preserved and prioritised through curriculum structures and learning activities.

At a programme level, this involves a shift in emphasis. It is not sufficient to focus solely on where and how AI tools are used; it is also necessary to ask: what features of the learning experience do we not want generative AI to replace, replicate, or diminish?

Some essential features of a modern learning environment might include:

- **Peer interaction and collaboration:** Design group tasks, problem-solving activities, and peer review processes that foster co-construction of knowledge.
- **Personalised feedback and dialogue:** Prioritise small group teaching, formative feedback opportunities, and open-ended tutorial discussions.
- **Development of academic identity and voice:** Create space for students to explain decisions, reflect on learning, and take intellectual ownership of their experience.
- **Challenge, uncertainty, and 'messy' thinking:** Encourage open-ended inquiry, problem formulation, and iterative drafts, not just polished and final outputs.

Bloom's Level	Examples of Generative AI Use	Purpose in Learning Progression	Example Assignment Brief
Remembering	Generate glossaries, flashcards, or summary notes from lecture content; retrieve definitions or formulas.	Support foundational knowledge and initial engagement with subject content.	<i>Use a generative AI tool to produce definitions for 10 core terms in real analysis (for example, limit point, bounded sequence, convergence, supremum, uniform continuity). Cross-check each with lecture notes and textbooks and annotate where clarifications or corrections are needed.</i>
Understanding	Ask for simplified explanations of difficult concepts; translate terminology into everyday language; paraphrase key ideas.	Build conceptual understanding and confidence in interpreting core ideas.	<i>Choose two mathematical concepts introduced this week and use generative AI to produce simplified explanations for each. Evaluate the explanations and write a short reflection on how your understanding developed.</i>
Applying	Generate practice questions or step-by-step examples; explore different applications of known techniques.	Enable practice and reinforcement of taught skills through self-directed learning.	<i>Ask a generative AI tool to create three practice problems on integration by substitution. Solve each problem, annotate your working, and evaluate the accuracy of the generated examples.</i>
Analysing	Compare alternative solutions generated by AI; identify flaws or omissions in AI-produced reasoning.	Encourage deeper engagement with content and methods; develop critical thinking.	<i>Use generative AI to solve a first-order differential equation using two different methods. Compare the outputs and analyse which is more complete, rigorous, or appropriate. Identify any mathematical inaccuracies or shortcuts.</i>
Evaluating	Critique AI-generated arguments, explanations, or code; assess reliability and accuracy; choose the most appropriate output.	Promote judgment, reflection, and academic independence in evaluating outputs.	<i>Submit an AI-generated proof of a standard result (for example, the sum of an arithmetic series). Annotate it to highlight correct reasoning, questionable logic, or missing justifications. Suggest improvements and justify your changes.</i>
Creating	Use AI to brainstorm ideas, draft outlines, or develop project scaffolds; refine outputs through iterative prompting.	Support originality, synthesis, and extended inquiry at advanced levels of study.	<i>Use a generative AI tool to help draft a mathematical modelling problem relevant to your discipline. Refine the prompt to include constraints, assumptions, and possible solution strategies. Submit a project outline and a reflective commentary on your use of AI in the design process.</i>

Table 1: Illustrative tasks for AI-Integrated mathematics teaching and assessment. Bloom's taxonomy levels are aligned with examples of generative AI use in mathematics, highlighting how AI can support progression from foundational understanding to advanced thinking. Assignment briefs illustrate practical ways to integrate these approaches into teaching and assessment design.

But good learning design also requires coherence and clarity. The integration of generative AI within a programme cannot be left solely to individual modules or their associated leads. While local flexibility is essential, students should experience a consistent and intentional approach across the curriculum. Without this, they may encounter contradictory guidance, unclear expectations, or unintentional inequities in learning opportunities.

Programme-level coherence does not require uniformity. It calls for transparency and shared intent. Programme teams should work together to map where generative AI is used across the curriculum, identify which skills or learning outcomes its use is designed to support, and agree on consistent language and expectations for appropriate use. These shared principles should be clearly communicated to students through handbooks, module guides, and digital platforms, thereby ensuring expectations are understood and reinforced across contexts. For example, one module might explicitly allow students to use generative AI to explore problem structures or generate graphs, while another prohibits its use in take-home assessments to protect independent reasoning. These differences are pedagogically valid, but only if students understand *why* the approaches differ and how they relate to the learning outcomes. Designing for generative AI is not simply a question of access or policy, it is a question of educational design. It is about creating a learning environment in which students use AI to enhance their experience, not escape from it. By embedding these values and structures into programme-level thinking, institutions can ensure that generative AI contributes positively to a vibrant, relational, and coherent student learning experience.

2.3. Ethical Use and Acceptable Behaviour

With the widespread availability of generative AI tools, clear expectations around acceptable and ethical use are essential. These expectations must be communicated at programme level, not left to the discretion of individual module leads. Without a shared understanding of when and how AI use is appropriate, students are likely to encounter inconsistent messages, leading to confusion, anxiety, or unintentional breaches of academic integrity. Programme teams should agree on a common framework for communicating acceptable use, with flexibility for disciplinary nuance. This framework should be introduced to students early, ideally during yearly inductions and core tutorial sessions, and reinforced through programme handbooks, module virtual learning environment (VLE) pages, and assignment briefs. Tutorials or in-module sessions can also be used to support students in using generative AI to understand marking criteria, interpret assessment briefs, or plan their approach, thereby making the AI use itself a designed part of early-stage preparation.

Each piece of formative or summative assessment should include an explicit statement about the permitted level of generative AI use, using a shared classification system. This enables consistency across modules and clarity for students.

2.3.1. Academic Integrity Frameworks

Some programmes may prefer a three-level ‘traffic light’ model for its clarity and ease of communication, such as that shown within Table 2. While this model is useful for setting broad expectations, it may not offer sufficient detail for complex tasks, particularly where partial use (for example, grammar correction vs. content generation) must be clearly distinguished. In these cases, a five-level model offers more nuance and can help students better understand how to use AI responsibly in both preparation and submission; such an example is shown within Table 3.

Level	Description	Permitted AI Use	Example
Prohibited	No use of AI tools allowed at any stage.	None	Handwritten closed-book exam.
Permitted with Limits	AI can support preparation (for example, idea generation, brief analysis) but not any submitted work.	Use to explore topics or understand criteria.	Use AI to help unpack a problem brief but write the solution independently.
Encouraged	AI is allowed in both preparation and submission, as part of the learning process.	Integrated use with expected, critical engagement.	Draft a reflective blog post with AI assistance, noting prompts and revisions.

Table 2: Three-level model for generative AI use within assessment. A simplified framework for categorising acceptable, cautious, and prohibited uses of generative AI in student assessment, designed to promote clarity and consistency.

Level	Description	Permitted AI Use	Example of Generative AI Use
1. Prohibited	Generative AI must not be used at any stage, including preparation.	None	None allowed: In-person exam with no internet access.
2. Preparation Only	Students may use AI in preparing for an assessment but not in any submitted work.	Use to clarify the brief, understand criteria, or explore task structure.	Use AI to summarise the brief and generate initial ideas, but write the essay independently.
3. Basic Skills Support	AI may assist with surface-level editing or rephrasing, but not substantive content.	Grammar checking, spelling, formatting.	Use Grammarly or rewording tools to improve clarity.
4. Research and Exploration	AI may support summarising content, identifying key ideas, or proposing structures, but students must produce original work.	Summarising sources, suggesting proof structures.	Use AI to generate a solution outline for a mathematics problem, then develop your own formal proof.
5. Collaborative Partner	Generative AI is used as a co-creator or content partner throughout the task. Students are expected to engage critically, reflect on their use, and evaluate the quality and appropriateness of AI contributions.	Co-produced content, iterative drafting, experimentation and critique with full documentation.	Use generative AI to support the development of a mathematical model. Submit the AI-supported work along with a reflective commentary evaluating its accuracy, limitations, and your decisions during the process.

Table 3: Five-level model for generative AI use within assessment. An extended version of the traffic light model that offers greater nuance in defining levels of permitted generative AI use, from preparatory support to full collaboration.

While the three-level model may be appropriate in some contexts, the five-level scale provides greater pedagogical transparency and practical flexibility, especially where assessment types vary, or students are required to reflect critically on their use of AI tools. What matters is that students understand *why* the boundaries exist and that expectations are both fair and transparent. For example, if students are permitted to use AI to understand the marking rubric or assessment structure, that should be made explicit. Equally, if students are expected to demonstrate unaided reasoning or construction, that too must be made clear.

Importantly, if the use of generative AI is prohibited, it is not sufficient to simply state this in guidance and place the responsibility for its non-use entirely on students. The assessment must be designed in such a way that AI use is not practically possible. This may involve using proctored examinations, timed in-person assessments, or Vivas that require explanation and justification. Prohibition, like permission, is a *design decision*, and it carries a responsibility to ensure that conditions support the intended learning and outcomes. Educators should also model transparency by being open about their own use of AI in teaching and feedback and by encouraging dialogue around its use. Just as we scaffold the development of academic writing, we must now scaffold students' capacity to engage with generative AI responsibly.

In the context of a tiered permissions model, institutions should clearly distinguish between undeclared but permitted use of AI and inappropriate use of AI in restricted assessments. Where students fail to reference AI use in a permitted task (for example a 'green' assessment), this would be better addressed through grading criteria and feedback, rather than formal academic integrity processes. Expectations around AI use, such as the inclusion of prompts, outputs, or a reflective commentary, should be clearly stated in the assignment brief and rubric, allowing educators to respond transparently and proportionately.

While tiered frameworks can provide valuable clarity and promote consistency, they are not a comprehensive solution. In practice, students may interpret expectations differently or misjudge the boundaries between levels, and simplified models such as traffic-light systems risk oversimplifying the nuanced realities of responsible AI use. These frameworks should therefore be regarded as tools to support dialogue and reflection, rather than as definitive mechanisms for ensuring compliance.

Programmes should also consider student development and confidence when applying these expectations, recognising that Year 1 students may require greater scaffolding and more formative feedback, while final-year students are expected to demonstrate mature, accurate, and transparent use.

Formal academic integrity investigations should be reserved for cases where students attempt to present AI-generated work as their own in contexts where its use is explicitly prohibited, and where there is evidence of deliberate intent to deceive. This pragmatic distinction helps ensure that students are held accountable for integrity breaches, without penalising poor documentation or unintentional misjudgements in otherwise open tasks.

2.3.2. Citing and Acknowledging Generative AI Use

Where students are permitted to use generative AI in assessments, they should be required to clearly acknowledge this use. Transparent attribution supports academic integrity, helps tutors understand how students have engaged with AI, and promotes reflective practice. Citation practices should be agreed and communicated at programme level so that students receive a consistent message across modules. Options include:

- A brief declaration at the end of a submission (for example, “*I used ChatGPT to generate a draft of the introduction, which I then revised*”).
- A dedicated section or appendix for more substantial use (for example, reflecting on how AI supported model development or argument structure).
- Including prompts or AI outputs (for example, screenshots) where appropriate.

Some institutions recommend referencing AI tools according to standard academic styles (for example, APA or Harvard), but consistency is more important than formality. What matters is that students understand when and how to declare use, and that staff are equipped to fairly assess the appropriateness of that use (if any).

2.3.3. Assured and Exploratory Credits: A Programme-Level Approach

As generative AI becomes increasingly embedded within the learning environment, ensuring that assessments can genuinely demonstrate students’ unaided capabilities is both challenging and necessary. While prohibiting AI use outright may be impractical or undesirable across an entire programme, there remains value in maintaining a secure foundation of independent academic performance. To address this, programmes may adopt a balanced approach, distinguishing between *Assured Credits* and *Exploratory Credits*.

Assured Credits refer to a defined portion of a programme, recommended as a minimum of one-third of total credits, where assessments are deliberately designed to ensure students demonstrate knowledge and skills without the use of generative AI tools. For a 120-credit per year programme, this would equate to 40 credits annually. These assessments provide assurance that part of the degree has been completed independently, supporting progression and award decisions.

This approach shifts the responsibility for securing unaided assessment from individual students to programme design. By embedding Assured Credits within the programme structure, teams can balance innovation and integrity, enabling the remaining credits, so-called *Exploratory Credits*, to support more open, creative, and AI-enabled assessment approaches. This distinction creates space for students to develop critical, ethical, and effective use of generative AI, without compromising the validity of academic achievement.

Assured Credits do not prescribe specific assessment types but define a minimum secured volume of assessment. Departments can determine the most appropriate methods, which might include proctored in-person examinations, supervised practicals, interactive oral assessments, or other formats suited to the discipline. The emphasis is on ensuring that these credits are assessed under conditions that prevent unauthorised AI use.

By incorporating both Assured and Exploratory Credits at programme level, institutions can foster a transparent and coherent approach to generative AI. Students benefit from clarity, equity, and a structured environment in which they can both demonstrate independent academic performance and develop the confidence to use AI tools responsibly and reflectively as part of their broader learning journey.

2.4. Respecting the Discipline: AI Use in Context

The appropriate use of generative AI is not universal, it must be shaped by the norms, values, and methods of each discipline. What is considered useful or ethical in one subject may be inappropriate or even counterproductive in another. For this reason, decisions about how and when generative AI

is integrated into learning and assessment must be grounded in disciplinary thinking and pedagogical purpose.

In the mathematical sciences, for example, the focus is often on formal reasoning, symbolic manipulation, conceptual clarity, and rigour. While generative AI tools can produce worked examples, draft solutions, or simplified explanations, their outputs frequently lack the logical transparency, precision, or notation required in formal mathematics. They may present incorrect arguments confidently, omit crucial reasoning steps, or misrepresent the structure of a proof. As such, they cannot replicate the process of mathematical thinking, abstraction, or justification that underpins deep understanding. Because of these limitations, generative AI is often more appropriate in exploratory, formative, or diagnostic tasks, rather than in summative assessments where students must demonstrate reasoning for themselves. For instance, students might use AI to compare solution strategies and identify inconsistencies, test informal AI explanations against lecture-based formal proofs, explore prompts to refine definitions, or critique mathematical writing generated by AI for errors or ambiguity.

By contrast, in disciplines such as design, education, or the humanities, generative AI may more naturally support brainstorming, planning, or synthesis, provided students critically evaluate outputs and integrate them into their own intellectual framework. Here, fluency with AI tools might form part of disciplinary development in a more explicit, and perhaps convenient, way.

To support students effectively, programme teams should consider:

- The types of thinking, knowledge construction, and communication that the discipline values.
- How generative AI can support, extend, or potentially undermine those capabilities.
- How tasks can be designed to reveal the limitations of AI as well as its potential, encouraging critique, comparison, and reflection.

The aim is not simply to decide whether generative AI is ‘allowed’, but to help students understand what kind of learning tool it is, and when, how, and why it may or may not be appropriate. This is a key part of developing disciplinary judgement and academic identity. In mathematics, this means helping students understand that while generative AI cannot replace active engagement with proofs, problem solving, or symbolic reasoning, it may play a useful role in surfacing misconceptions, provoking dialogue, and sharpening their thinking through critique.

2.4.1. Examples from the Mathematical Sciences

The following examples seek to illustrate how generative AI can be integrated into learning of the mathematical sciences within higher education in ways that reflect and complement disciplinary thinking:

- **Error identification task:** Students are given an AI-generated solution to a calculus problem (for example, finding a local maximum using the second derivative). They must identify conceptual errors or procedural shortcuts, and rewrite the solution in full, justifying each step. *Focus: understanding critical features of differentiation and reasoning structure.*
- **Compare and contrast proofs:** Students prompt a generative AI tool to produce a proof of the Cauchy Integral Theorem, then compare this with the formal proof provided in lectures or a recommended text. They annotate both versions to highlight missing assumptions, issues

in logical progression, or differences in formalism and explanatory clarity.
Focus: developing proof fluency, critical evaluation, and understanding of complex analysis.

- **AI as an exploration tool:** Students use generative AI to explore different formulations of a mathematical concept (for example sequences vs. series), then critique which explanation is most helpful, precise, or misleading. This might be used as part of a tutorial or paired activity to generate discussion.
Focus: conceptual understanding and meta-cognition.
- **Model generation with reflection:** In a mathematical modelling task, students may use AI to generate initial ideas or explore variable relationships. They must document their use of AI, justify modelling decisions, and reflect on how the AI outputs influenced their thinking.
Focus: transparency, applied problem solving, reflective practice.

These activities position generative AI not as a shortcut to achieving 'correct' answers but as a dialogue partner, a source of challenge, or a thinking scaffold. They also help develop critical awareness of where AI fails to meet disciplinary expectations, turning limitations into new learning opportunities.

2.5. Digital and AI Literacy

Generative AI skills are now a fundamental part of broader digital and academic literacies. Students need support not only in accessing tools, but in understanding how to use them thoughtfully, critically, and appropriately. This includes recognising where AI tools are embedded in common platforms and how they may shape learning behaviours, skill development, and academic outputs. A structured approach to developing AI literacy might include:

- **Introductory sessions** on how generative AI works, and its strengths and limitations.
- **Practical workshops** on prompting, critiquing outputs, and recognising misuse or over-reliance.
- **Embedded learning tasks** that require students to reflect on their own use of generative AI.
- **Comparative exercises** analysing human- vs AI-generated work to explore quality, rigour, and disciplinary fit.

Importantly, these opportunities should be embedded throughout a programme, not confined to induction events or optional study skills modules. Digital literacy is developmental, and students need repeated, supported experiences over time to become confident and critical users.

2.5.1. Awareness of Embedded AI Tools

An increasingly complex challenge is that generative AI is becoming invisible, integrated into tools students already use daily, often without them, or educators, realising AI is involved. For example:

- Grammarly now offers rephrasing, content suggestions, and tone control. All functions powered by generative AI.
- Microsoft Copilot in Word, PowerPoint, and Excel provides AI-generated summaries, auto-generated text, and data insights.

- Overleaf, a common platform in mathematics and technical disciplines, has introduced AI-based LaTeX content generation and document suggestions.
- Google Workspace includes generative features in Docs and Slides.

This blurring of boundaries raises critical questions: Are students aware when they are using generative AI? Do they know when and how to declare it? Are staff able to distinguish between tools that are permitted and those that aren't?

As generative AI becomes increasingly embedded, and often hidden, within common software platforms, supporting students to use these tools responsibly is more important than ever. Programme teams have a responsibility to help students recognise when generative AI is being used, even if it is not explicitly labelled, and to understand how such use aligns with institutional policies and expectations for assessment. Crucially, students also need space to reflect on how these tools influence their own thinking, writing, or problem-solving processes. This means supporting students in making informed decisions about the tools they already use, especially where the lines between traditional functionality and AI-generated content is becoming increasingly blurred. Programme teams should therefore provide clear guidance on:

- Whether such tools are permitted for preparation or submission.
- How to differentiate between surface-level features (such as formatting or syntax) and AI-generated content.
- Where assessment briefs and module handbooks should be updated to reflect these evolving capabilities.

Supporting AI and digital literacy is no longer an optional enhancement, it is part of the shared responsibility of curriculum design. The goal is not only to ensure technical competence, but to help students develop ethical, reflective, and academically grounded approaches to AI as part of their learning journey.

2.5.2. Access and Equity

As generative AI tools become more embedded in higher education, equity of access and confidence must be a core design consideration. Not all students begin from the same place. Some may be unable to purchase premium tools, while others may lack regular access to suitable devices or browsers. For many, the challenge lies not in access alone, but in navigating unfamiliar platforms, interpreting complex outputs, or using the tools effectively, particularly if they are working in a second language or are less confident with academic conventions. These disparities risk compounding existing inequalities unless addressed through inclusive programme and institutional design. Crucially, equity in AI use is not just about access, it is also about confidence, transparency, and support.

To promote equity and inclusive participation, programme teams and institutions should:

- **Prioritise free and accessible tools:** Where possible, design learning tasks that can be completed using open-access platforms such as ChatGPT (free tier), Microsoft Copilot (available through the Edge browser), or Google Gemini. Tasks should not reward students for having access to more advanced or premium tools but instead focus on how well they engage with the learning process itself.

- **Promote institutional licences:** Ensure students are aware of centrally supported tools, such as Grammarly (for writing support), GitHub Copilot (for code generation), or subject-specific tools like Wolfram Alpha or Wolfram Chat. A mathematical sciences programme might offer workshops showing how Wolfram tools can be used to explore symbolic algebra or graph functions safely and effectively.
- **Support onboarding:** Provide students with guidance documents, annotated screenshots, or short demonstration videos that walk through how AI tools can be used within academic tasks. For instance, a screencast might show how to use Copilot in Overleaf to generate LaTeX-based mathematical expressions, highlighting what's appropriate for preparation and what must be original.
- **Offer alternatives:** Design tasks that allow students to meet learning outcomes with or without AI. For example, if one option involves prompting an AI tool to generate model solutions, an alternative might allow students to use worked examples from lecture notes or textbooks, combined with their own commentary or analysis.
- **Avoid hidden advantage:** When setting assignments, consider whether access to premium tools (for example, GPT-4, paid statistical plugins, or advanced coding assistants) might confer unfair advantage. This might mean standardising the tool expected for a task or clearly stating that outputs must be human-authored, even if AI is used during preparation.

These principles apply not only in formal assessments, but in everyday learning. Embedding low-stakes, supported opportunities for experimentation, such as peer-led discussions, tutorial activities, or scaffolded practice, can help normalise AI use and build collective confidence. Wherever possible, AI-related activities should be designed so that any permitted tool can be used effectively. This not only promotes inclusion but ensures that equity concerns don't unintentionally reinforce existing gaps in access, confidence, or engagement.

Illustrative Example 1: Building a Glossary Using AI in Year 1 Mathematics

As a foundation-level task, students use a generative AI tool to produce draft definitions for ten key mathematical terms relevant to their course, such as *surjection*, *convergence*, and *basis*. Students are encouraged to treat the AI output as a starting point for critical engagement.

They then:

1. Refine each definition using lecture notes, textbooks, or other trusted resources.
2. Provide examples to illustrate each term in context.
3. Submit both the revised glossary and a brief reflection describing how the AI-generated definitions were improved or clarified.

This task supports the development of mathematical language, conceptual understanding, and early AI literacy in a low-stakes, formative setting.

3. Designing Learning Experiences

Integrating generative AI into learning design is not simply about introducing new tools, it is about reshaping how students engage with knowledge, build understanding, and develop academic confidence. Just as assessment design must be reconsidered in the context of AI, so too must the learning experiences that underpin it. When used well, generative AI can support students in asking better questions, exploring alternative approaches, receiving personalised feedback, and practising

at their own pace. However, these benefits are only realised when learning activities are deliberately designed to take advantage of what AI can offer. As with any educational tool, its value depends entirely on how it is used.

Effective design of AI-supported learning should be intentional, transparent, and clearly aligned with learning outcomes. Students need to understand why generative AI is being used in a particular task, and how it supports the development of specific knowledge or skills. Activities should prompt critical engagement with AI outputs, encouraging students to question, interpret, and evaluate what they are given, rather than passively accept it. Crucially, the use of AI must not replace the essential human elements of meaningful learning: dialogue, feedback, collaboration, and productive struggle must remain central to the learning experience.

At programme level, coordination is key. Educators should not assume that AI use in learning will emerge organically or be consistent across modules. Programme teams should work collaboratively to map where AI-supported learning is already happening, identify gaps or opportunities for experimentation, and ensure that students encounter a variety of AI interactions throughout the curriculum, from exploratory practice to critical analysis to co-creation.

3.1. Roles Generative AI Can Play in Enhancing Student Learning

One helpful way to think about how generative AI can be integrated into learning is to consider the role it can potentially play within a given task. Sharples (2023), and expanded within Sabzalieva and Valentini (2023), outlines a set of pedagogical roles that AI might adopt, depending on how educators design learning activities. These roles are not mutually exclusive, students might move between several within a single task, but asking “*What role might (or do) I want AI to play in this activity?*” is a useful initial design prompt for educators.

AI Role	What it Does	Mathematics-Specific Example
Possibility Engine	Suggests alternative ideas or expressions	A student exploring methods to solve a system of equations prompts AI to suggest alternative approaches (for example, substitution, matrix methods, graphical). In statistics, AI proposes different visualisations (boxplot, histogram, violin plot) for summarising a dataset.
Socratic Opponent	Challenges thinking with counterpoints or questions	A student preparing a proof involving irrational numbers tests it against AI by asking for potential flaws or counterexamples. In a statistics context, students use AI to generate critiques of a sampling method or challenge assumptions in an experimental design.
Collaboration Coach	Supports group problem solving and information gathering	A student group working on a final-year project asks AI to suggest types of regression models suitable for predicting housing prices, then compares AI's suggestions with academic sources.
Guide on the Side	Provides scaffolding or suggestions	While tackling an unfamiliar integration problem, students ask AI for a hint on which substitution might be useful, without being shown the full solution.
Personal Tutor	Offers feedback on progress or draft responses	A student submits a worked solution to a proof involving induction and asks AI to spot gaps in the logical progression. In statistics, AI reviews a student's draft report and suggests improvements to the interpretation of p-values.

Co-designer	Assists in developing plans or tasks	A student working on a mini project in applied mathematics uses AI to structure a comparison between exponential and logistic growth models, identifying variables and expected behaviour. In statistics, students use AI to design a small survey and plan how they will clean and visualise the data.
Exploratorium	Prompts experimentation and discovery	Students vary parameters in a function and use AI to help visualise the resulting graphs, investigating how changes affect continuity or convergence. In statistics, students use AI to simulate repeated sampling from different distributions and observe variability.
Study Buddy	Supports revision and retrieval	AI quizzes a student on key theorems in real analysis, generating practice problems with varying difficulty. In statistics, it generates true/false questions on hypothesis testing assumptions.
Motivator	Offers challenges and gamified learning prompts	AI provides a set of logic puzzles that become progressively more complex and aligned with the week's learning. In statistics, students ask AI to create a challenge sequence for interpreting confidence intervals under time pressure.
Dynamic Assessor	Helps track learning and identify gaps	A student asks AI to generate a concept map of their current knowledge in vector calculus. In statistics, a student reviews a sequence of AI-generated summary questions to identify weak areas in their understanding of correlation and causation.

Table 4: Roles of Generative AI in Mathematics and Statistics Learning. *Adapted and extended from the work of Sharples (2023) and as presented in Sabzalieva and Valentini (2023), the roles outlined here demonstrate how generative AI can support mathematics and statistics learning by acting as exploratory partner, feedback provider, or dynamic assessor.*

3.2. Designing AI-Supported Learning Activities

The roles outlined in Section 3.1 can be translated into patterns of learning activity, that is structured ways in which students interact with content, ideas, and one another, with AI acting as a supporting presence. The following examples serve as adaptable templates for designing effective AI-enhanced learning tasks. Programme teams might use these to map existing AI-supported learning opportunities, identify new areas for exploration or reflection, and ensure alignment between learning activities and assessment practices.

3.2.1. Prompt-led Learning Tasks

(Related roles: Possibility engine, Personal tutor, Study buddy)

These tasks involve students prompting AI tools directly and interpreting the outputs. They support the development of procedural fluency and conceptual understanding, encouraging students to evaluate the clarity, accuracy, and educational value of generated content. Example activities might include:

- **Calculus:** Students use AI to generate five integrals involving substitution, solve each one, and explain which were well-constructed and which were misleading.
- **Set Theory:** Students prompt AI for an explanation of the difference between injective and surjective functions, then rewrite it to support peer understanding.
- **Real Analysis:** Students request definitions and examples of uniform convergence from AI, annotate the outputs, and evaluate their mathematical accuracy.

Illustrative Example 2: Prompt-Led Practice in Calculus

Students are introduced to substitution as a method for evaluating integrals and then tasked with using generative AI to create a set of integration problems designed to reinforce this skill. They prompt the AI to generate five definite or indefinite integrals that require substitution and solve each by hand.

Following this, students complete a short evaluative commentary where they:

1. Assess whether each integral is solvable using standard substitution techniques and identify any that were poorly constructed, ambiguous, or beyond the intended scope.
2. Reflect on whether the AI-generated questions matched the complexity and structure of problems typically encountered in class or assessments.
3. Highlight any potential misconceptions a learner might develop if they relied solely on the AI-generated questions, such as missing key constraints or misapplying substitution.

This task is used in a formative setting to support both procedural fluency and the ability to critically assess learning resources, helping students take ownership of their practice and develop a more evaluative relationship with the tools they use.

3.2.2. Reverse Engineering and 'Flipped' Learning

(Related roles: Socratic opponent, Dynamic assessor, Guide on the side)

These tasks involve students analysing, critiquing, or correcting AI-generated responses. They develop deeper reasoning, logical clarity, and confidence in academic argumentation. Example activities might include:

- **Mathematical Logic:** Students prompt AI to prove De Morgan's Laws, critique the logic, and write a corrected version with explanations.
- **Probability Theory:** Students prompt AI to calculate and explain the expected value of a discrete random variable. They then critique the explanation, correct any misconceptions, and rewrite the reasoning to meet formal statistical standard.
- **Differential Equations:** Students prompt AI to solve a first-order differential equation using an integrating factor. They are then asked to verify the steps, identify any shortcuts or incorrect assumptions, and rewrite the solution to include all working and justifications expected at university level.

Illustrative Example 3: Clarifying Statistical Misconceptions

Students are asked to use generative AI to produce explanations of fundamental statistical concepts, such as *p-values*, *confidence intervals*, or *correlation vs. causation*. They are then required to critique and refine the output to develop a deeper understanding of both the concept and its appropriate communication. Students complete the following steps:

1. Identify inaccuracies, oversimplifications, or common misconceptions present in the AI-generated explanation (for example, implying that a p-value indicates the probability the null hypothesis is true).
2. Rewrite the explanation using statistically rigorous language suitable for a first-year audience, drawing on taught materials and trusted resources.
3. Reflect on why the original explanation was misleading, and explain how their revision provides a clearer, more accurate interpretation.

The final output includes both the original AI response and the revised version, annotated with brief justifications. This activity supports the development of statistical reasoning, precision in communication, and the critical appraisal of AI-generated content, particularly in contexts where inaccurate explanations may be persuasive but flawed.

3.2.3. Personalised Exploration and Practice

(Related roles: Exploratorium, Study buddy, Personal tutor)

These tasks help students tailor AI use to their individual learning needs, generating practice material, summarising concepts, or quizzing themselves on areas of weakness. They support metacognitive development and build learner independence. Example activities might include:

- **Differential Equations:** Students prompt AI to explain the difference between homogeneous and non-homogeneous ODEs, then generate and solve related problems.
- **Mathematical Logic:** Students use AI to test different truth table structures for logical equivalence and evaluate which best support their learning.
- **Descriptive Statistics:** Students ask AI to generate small datasets that illustrate specific statistical concepts, such as skewness, outliers, or variance. They then calculate summary statistics by hand, interpret the results, and reflect on how well the AI-generated data meets the original brief.

Illustrative Example 4: Personalised Practice with Generative AI

Students identify specific areas of weakness or uncertainty in their mathematical understanding, such as techniques in integration, properties of sequences, or interpreting statistical output. Using a generative AI tool, they prompt the system to produce relevant practice questions tailored to those areas. They then select at least two examples to solve independently, followed by a structured evaluation in which they:

1. Assess whether the generated material was accurate, relevant, and appropriately challenging for their level.
2. Reflect on how helpful the AI was in reinforcing concepts or clarifying misunderstandings.
3. Identify any misconceptions or over-simplifications introduced by the AI, and consider how they might affect learning if left unchallenged.

This task encourages metacognition, supports independent study, and helps students take greater ownership of their learning. It also introduces opportunities for dialogue in tutorials - comparing questions, evaluating usefulness, or exploring how prompts shape outcomes.

3.2.4. Simulated Dialogue and Peer Learning

(Related roles: Socratic opponent, Collaboration coach, Motivator)

These activities simulate academic dialogue or collaborative reasoning, enabling students to practice articulating ideas, debating alternatives, and responding to critique. They prepare students for tutorials, group work, or oral assessments. Example activities might include:

- **Number Theory:** Students ask AI to 'disagree' with their conjecture about a divisibility rule and use the resulting dialogue to identify limitations or counterexamples. They then revise their conjecture and test it with peers.
- **Mathematical Modelling:** Groups use AI to generate and evaluate assumptions for a population model, deciding collaboratively which to adopt and why.
- **Abstract Algebra:** Students role-play a dialogue with AI around whether a non-zero ring with no multiplicative identity can still be a ring. The conversation becomes the basis for class discussion and clarification of formal axioms.

Illustrative Example 5: Simulated Dialogue in Abstract Algebra

Students use AI to investigate whether a particular mathematical structure satisfies the group axioms. They engage the AI in a structured dialogue about a proposed set and operation, for example, the set of 2×2 invertible matrices under matrix multiplication. Students are asked to:

1. Prompt AI to assess the group properties (closure, associativity, identity, and inverse) for the chosen structure.
2. Identify and annotate points of agreement or disagreement with formal mathematical reasoning.
3. Rewrite the conversation as a structured proof, highlighting where AI responses were helpful, incomplete, or misleading.

This task develops deeper understanding of abstract structures, encourages critical evaluation of mathematical reasoning, and promotes confidence in formal proof-writing through dialogic exploration.

3.3. Framing AI as a Learning Partner

Designing learning experiences that make effective use of generative AI is not about automating teaching, it is about expanding the ways students can practise, test, and deepen their understanding. When used well, these tools offer new spaces for exploration, experimentation, and feedback. The goal is not to replace the learning process but to enhance it, making space for students to engage more meaningfully with ideas and develop confidence through practice.

Critically, this requires more than ad hoc integration at the module level. It calls for intentional programme-level design, where the use of AI is scaffolded, aligned with learning outcomes, and supported through dialogue, reflection, and inclusive practices. When designed in this way, generative AI becomes not a threat to teaching, but a partner in learning, helping students build knowledge, question assumptions, and take ownership of their academic journey.

4. Designing Assessment

Effective assessment is a cornerstone of good programme design. In an era of generative AI, the need for diverse, inclusive, and well-aligned assessment strategies has never been more urgent. While much of the national and institutional focus has centred on the risks AI poses to traditional forms of assessment, there is also significant opportunity to rethink the purpose and value of assessment within a programme.

Not every assessment needs to be written. Not every task needs to be individual or unseen. A well-designed programme will expose students to a range of assessment types, oral, visual, practical, reflective, collaborative, aligned to the knowledge and skills the programme aims to develop. This variety encourages different modes of thinking and expression, offers more inclusive pathways for students to demonstrate their learning, and reduces over-reliance on any single format that may be particularly vulnerable to automation.

The detailed pedagogical challenges and design implications of assessment in the context of generative AI are explored in greater detail within Grove (2024). This section draws on and complements that work, focusing on practical ways to support programme-level coherence and the integration of AI into assessment practices in mathematics and beyond.

4.1. Assessment Design and Bloom's Taxonomy

Bloom's taxonomy offers a useful framework for understanding the types of thinking that assessment tasks aim to elicit. While tasks at the lower levels, such as remembering or basic comprehension, can now be completed more easily using generative AI tools, this only strengthens the case for designing assessments that promote higher-order thinking. Tasks that require students to apply their knowledge in new contexts, solve problems, evaluate alternatives, make reasoned decisions, or produce original work are increasingly important in an AI-enabled learning environment. At the same time, focusing on these higher-level skills does not mean abandoning the lower levels; rather, it affords opportunities to consolidate foundational knowledge through meaningful application, helping students reinforce core concepts in more authentic and challenging contexts.

Table 5 shows a set of mathematics-focused assessment examples aligned with different levels of Bloom's taxonomy. Each example illustrates how AI might be used either as a tool within the task or as a feature for students to critique and build upon.

These examples demonstrate that the use of AI in assessment is not inherently problematic, but the purpose of the assessment must be clearly communicated. Students should know whether AI use is permitted, what form that use can take, and how it should be acknowledged (see Section 2). Just as importantly, they must understand what learning outcomes the task is designed to assess. This includes knowing whether the focus is on accuracy, reasoning, conceptual understanding, communication, or reflection. Without that clarity, students may unintentionally misuse AI or fail to demonstrate the very skills the assessment is intended to develop.

4.2. Flipped Assessment: An Example Approach

While assessment design has been discussed in more detail in previous work (Grove, 2024), it is important to reinforce here that integrating generative AI into learning requires a corresponding shift in how we design assessment. Assessments should not be disconnected from the tools and strategies students are using throughout their studies. If AI is part of their learning process, whether to generate examples, explain concepts, or simulate problem-solving, then assessment must evolve to account for that. The aim is not simply to permit or prohibit AI use, but to create assessment tasks

that require students to think critically, engage deeply with content, and demonstrate intellectual ownership of their work.

Cognitive Level	Assessment Task (Mathematics Example)	Use of Generative AI	Learning Purpose
Remembering	Define and explain key terms from Real Analysis using your own examples.	AI can provide initial definitions; students must personalise, extend with examples, and check accuracy.	Support terminology recall, concept clarification, and confidence-building particularly in early-stage learning.
Understanding	Explain the difference between pointwise and uniform convergence, with annotated diagrams.	Students use AI to draft an explanation, then refine it using lecture notes and annotate errors or omissions.	Promote conceptual understanding, diagrammatic reasoning, and the ability to identify nuance in formal explanations.
Applying	Solve a differential equation and apply it to a physical model (for example, cooling of an object).	AI may assist in exploring solution strategies during preparation; final submission must include full working and interpretation.	Encourage procedural fluency, application of methods to real-world contexts, and awareness of modelling assumptions.
Analysing	Compare two AI-generated solutions to a matrix problem. Identify strengths, flaws, and missing steps.	AI-generated solutions are integrated into the task; students focus on critique, logical coherence, and comparative reasoning.	Develop critical thinking, error detection, and understanding of valid mathematical argument structure.
Evaluating	Select a method to approximate an integral numerically. Justify your choice and discuss its limitations.	AI can suggest possible methods; students evaluate these, select the most appropriate, and explain the rationale in a structured report.	Foster evaluative judgement and decision-making between alternative mathematical techniques.
Creating	Design a mathematical model to represent population growth, stating assumptions and constraints.	Students brainstorm with AI to generate possible model forms, then document decisions, reflect on assumptions, and justify their final approach.	Support creative modelling, mathematical justification, and reflection on the use and limitations of AI in exploratory tasks.

Table 5: Generative AI Use Across Levels of Bloom’s Taxonomy in Mathematics Assessment.
This overview illustrates how assessment tasks in mathematics can be designed to align with Bloom’s taxonomy while integrating generative AI in purposeful and pedagogically appropriate ways

One possible approach is a '*flipped assessment*' model. In this design, students begin with AI-generated content but are assessed on their ability to interrogate, adapt, and improve that content. Rather than focusing solely on producing work from scratch, students are asked to demonstrate higher-order understanding through critique, transformation, and reflective commentary. This model mirrors professional and academic practice. Rarely are problems in research or the workplace solved in isolation or from a completely original starting point. Mathematicians and scientists often refine flawed solutions, test assumptions, adapt known structures, or improve clarity and precision. These are valuable academic and graduate skills, and ones difficult to outsource to AI.

Illustrative Example 6: Validating GAI Solutions in Linear Algebra

Students are provided with a generative AI-produced solution to an inverse matrix problem. The AI's output may include notational errors, omitted justifications, or incorrect interpretations.

Students are tasked to:

1. Identify any inaccuracies or inconsistencies in the solution.
2. Annotate the solution using correct mathematical notation and terminology.
3. Compare the AI's method to their own and provide a written justification of any differences in approach or interpretation.
4. Identify the key underpinning mathematical ideas that are fundamental to successful understanding (for example, if the inverse matrix is multiplied by the original matrix, the identity matrix should be obtained).

This task helps students practise rigorous notation, clarify common misconceptions, and strengthen their understanding of eigenvalue problems through critique and comparison.

Flipped assessment is not about reducing expectations and standards; it is about shifting them. It positions students as critical users of AI, not passive consumers, and it rewards intellectual control, insight, and precision. At a programme level, this approach can help scaffold students' engagement with generative AI ahead of summative tasks, place greater emphasis on reasoning, analysis, and revision within assessment criteria, and prepare students for the evaluative demands of research and professional practice.

Illustrative Example 7: Flipping the Proof with Fermat

Students are asked to use AI to generate a worked solution to a question involving Fermat's Little Theorem (which in the notation of modular arithmetic is written as $a^p \equiv a \pmod{p}$) and which asks them to show that if a is not divisible by p , then Fermat's Little Theorem is equivalent to $a^{p-1} \equiv 1 \pmod{p}$. The AI output often omits that a must be coprime to the prime p . The student's task is to:

1. Review the AI-generated proof, appraising its accuracy, conciseness, and level of detail, and identifying any missing assumptions - especially the requirement that a and p be coprime.
2. Rewrite the solution correctly, including all necessary conditions and ensuring that the logic is clear and formally valid.
3. Reflect on why such errors are common in AI-generated mathematics and how they relate to formal mathematical reasoning.

This task assesses the student's understanding of proof structure, logical conditions, and the importance of precision - skills central to mathematical practice. Rather than producing a proof from scratch, which can readily be found online anyway, the student is challenged to diagnose, critique, and improve, demonstrating deeper engagement with the core mathematical concepts, ideas, and subtleties.

4.3. Aligning Assessment Criteria

As generative AI becomes increasingly embedded in higher education, our assessment criteria must evolve to reflect the changing demands of the discipline and the wider contexts in which disciplinary thinking is applied. At a programme level, this means re-evaluating the weight given to procedural tasks, such as routine calculations, symbolic manipulation, or reproducing standard techniques, and placing greater emphasis on deeper understanding, strategic thinking, and the ability to apply mathematical ideas flexibly and in increasingly novel contexts.

While fluency with core methods remains essential, assessment should highlight students' capacity to explain their reasoning, justify the choice of particular techniques, and apply concepts to unfamiliar or complex situations. Clarity of mathematical communication, through structured argument, precise notation, and effective use of visual representations, should be recognised explicitly in assessment criteria, reflecting the importance of conveying ideas clearly in both academic and professional settings. The use of real or simulated data offers opportunities for students to demonstrate interpretation and analysis, moving beyond abstract manipulation to more applied, context-rich problems. Criteria should also acknowledge the value of identifying and addressing errors, contradictions, or limitations in reasoning, whether through individual work or with support from tools such as generative AI. These tasks develop students' critical thinking and can help surface deeper mathematical understanding.

Incorporating reflective components, such as commentary on the decision-making process, the interpretation of AI-generated outputs, or the evaluation of multiple solution strategies, can further enhance students' metacognitive awareness. Project-based assessments and open-ended problems that emphasise problem formulation, modelling, and exploration provide authentic opportunities to assess how students think mathematically, not just what they can compute or remember. At a programme level, a consistent and transparent approach to updating assessment criteria can help students build confidence in what is valued across their learning journey and prepare them for evolving mathematical practice beyond university.

4.4. Coherence and Transparency at Programme Level

At a programme level, assessment design should be guided by shared principles that ensure coherence, progression, and transparency. Students should not encounter contradictory guidance about the use of generative AI in different modules; rather, programmes should present a consistent and clearly communicated stance. Alongside diverse assessment types, programmes may also include a defined proportion of Assured Credits (see Section 2.3.3) to ensure a baseline of unaided student achievement. These are complemented by Exploratory Credits, where students can engage more openly and reflectively with generative AI, supported by clear expectations and scaffolded practice. Assessment formats should evolve over the course of the programme, offering increasing complexity, independence, and opportunities for critical reflection. Alongside academic knowledge and disciplinary skills, students should also be supported in developing metacognitive awareness and ethical judgement, particularly in relation to how they engage with generative AI technologies.

Assessment remains one of the most powerful tools we have as educators to shape student learning. In an AI-enabled era, it is no longer enough to protect assessment from generative AI, we must instead design assessment in ways that respond to its presence and potential. When thoughtfully aligned to programme aims, assessment can encourage deeper engagement, foster independence, and prepare students for the intellectual and ethical demands of academic and professional life.

5. Supporting Students

Designing for generative AI at programme level involves more than embedding tools into teaching and assessment. It requires a commitment to supporting students as they develop the capacity to use these technologies independently, critically, and responsibly, both within formal learning tasks and beyond. This support must evolve over time. Generative AI is not static, and the ways students engage with it will change as tools develop, expectations shift, and confidence grows.

Programmes therefore need to provide sustained support that recognises generative AI as both a learning tool and a literacy. This includes helping students develop the judgement to evaluate when and how to use AI effectively, and when not to use it at all.

5.1. Independent and Responsible Use

Students across disciplines, including mathematics, are already using generative AI to support their learning. These tools offer instant explanations, walkthroughs of problems, auto-generated revision resources, and help with structuring answers. Used with discernment, they can encourage self-directed study, boost confidence, and provide flexible support. But the risks are real. Over-reliance on AI tools can inhibit the development of reasoning skills, mask misconceptions, or lead to the uncritical acceptance of flawed or superficial responses. To address this, programme teams should actively support students in using generative AI in independent study, not through prohibition, but through design.

Activities such as reflective logs, structured prompts, or tutorial discussions can help students consider when AI tools add value, and when they obscure understanding. Tutorials can incorporate short tasks that ask students to compare AI-generated summaries to lecture notes, explore whether an AI explanation would be suitable for a peer, or critique step-by-step solutions for gaps in reasoning. These small interventions help students treat AI as a companion to learning, not a shortcut.

Illustrative Example 8: Problem Deconstruction from AI Solutions

Students are given a differential equation generated and solved by an AI tool, and are challenged to work backwards to reconstruct the context in which the equation might have arisen.

Their task is to:

1. Infer the original problem scenario that could lead to the given equation (for example, population growth, thermal change).
2. Identify any missing boundary conditions, assumptions, or modelling steps.
3. Explore alternative ways the problem could be modelled and explain the reasoning behind those choices.

This activity supports higher-order modelling skills, critical engagement with AI outputs, and the development of a more intuitive understanding of differential equations in real-world contexts.

Programmes might also include short reflections in portfolios or module assessments, asking students to describe how they used AI, what limitations they found, and what strategies they would recommend to others. These kinds of reflective habits encourage ethical and thoughtful engagement with AI and offer staff valuable insight into student learning practices.

As part of developing students' understanding of generative AI, it is important to introduce the environmental and ethical dimensions associated with its use. This includes helping students critically reflect on the sustainability implications of large-scale AI models, such as their energy demands, data usage, and broader societal impacts. Students should also be encouraged to consider how to engage with generative AI in a responsible and sustainable manner, for example, using tools purposefully rather than excessively, and evaluating when their use adds value to learning or problem-solving.

Programmes should also acknowledge that some students will choose not to use AI. This may be due to uncertainty, ethical concerns, or a preference for traditional approaches. These students should be supported with reassurance rather than pressure. For some, the sheer number of tools can be overwhelming; others may feel the need to be constantly 'optimising' their study. Promoting thoughtful, balanced engagement with technology is an important part of supporting student wellbeing.

5.2. *Developing AI Literacy and Agility*

Generative AI is not a fixed technology. New tools, interfaces, and expectations are constantly emerging. Students need more than a one-off induction; they need a developmental approach to AI literacy, and one that treats it as part of their academic and professional skillset. Programmes can support this through a scaffolded model that revisits key principles throughout the curriculum:

- **Orientation:** Early in the programme, students should learn what generative AI is, how it works, and where it supports or conflicts with disciplinary values. This includes understanding ethical use, citation practices, and institutional expectations (for example, through the traffic-light frameworks outlined in Section 2).
- **Skill-building:** As students progress, they can be introduced to more advanced practices: writing purposeful prompts, comparing tool outputs, or identifying the strengths and weaknesses of AI-generated responses.
- **Critical engagement:** Advanced activities should involve not just using AI, but challenging it. For example, students might test the robustness of an AI-generated proof, annotate a flawed response, or reflect on how AI shaped their thinking.

Illustrative Example 9: Dialogue with a Mathematician

To explore mathematical concepts in a creative and reflective way, students are asked to simulate a scripted dialogue with an historical mathematician (for example, Ramanujan, Noether, Euler, or perhaps an exchange of letters between de Fermat, Wiles, and Taylor), using a generative AI tool to generate a first draft of the exchange.

They are then asked to:

1. Edit and expand the dialogue to ensure historical accuracy and mathematical clarity.
2. Include at least one moment where a misconception is corrected or challenged.
3. Write a short reflective commentary on what they learned, what surprised them, and how the exercise deepened their understanding of the concept or figure.

This task helps students humanise mathematical thinking, clarify misconceptions, and practise articulating mathematical ideas in dialogue form.

These opportunities can be integrated into discipline-based teaching or offered through co-curricular activities such as peer-led workshops or embedded tasks in tutorials and labs. Key is that they are iterative, revisited at multiple stages, and aligned to increasing expectations for independence, accuracy, and ethical awareness.

As discussed earlier in Section 2.5.2, equity and access must be central considerations when designing learning tasks that incorporate generative AI. These principles apply not only in structured teaching activities but also in the independent and informal ways students engage with AI tools. Programmes should continue to embed opportunities for low-stakes experimentation, peer learning, and reflection, ensuring that all students feel confident and supported, regardless of prior experience or access.

5.3. Supporting Students Who Choose Not to Use Generative AI

While much of this framework focuses on enabling students to use generative AI effectively and responsibly, it is equally important to support those who choose *not* to engage with such tools. Some students may have ethical or environmental concerns, others may be cautious about academic integrity risks, and some may simply prefer to develop skills through more traditional approaches. These choices should be respected and supported as part of an inclusive learning environment.

One of the most practical ways to ensure inclusivity is through flexible assessment design. Tasks should allow students to meet the intended learning outcomes without requiring generative AI. For example, where one option invites students to prompt an AI tool to produce content for critique, an alternative should be available that draws on lecture materials, textbooks, or staff-provided examples. Time and workload assumptions also require careful consideration. Some students may choose not to use AI tools to accelerate or automate stages of their work, such as research, summarising, or drafting. Assessment briefs should avoid implicitly privileging AI-enabled efficiency. Timelines and expectations should be realistic for students completing all tasks manually.

Where AI-generated materials are used in teaching or assessment, it can be helpful to provide optional resources so that students are not required to use a tool themselves; pre-prepared examples, for instance, can ensure learning parity while preserving autonomy. This principle also extends to feedback and peer interactions, where it is important not to assume all students have used AI tools. In both formative and summative contexts, staff should recognise and respect different approaches, including deliberate non-use, and avoid presenting AI use as inherently more advanced or effective. While showcasing examples of productive AI use can be helpful, this should be balanced with recognition of strong work produced without it. More broadly, acknowledging that non-use is a valid position can support confidence and wellbeing. Students should feel able to articulate their approach, whether in reflective writing, one-to-one settings, or portfolio commentary, and thoughtful non-use should be positioned as an intellectually engaged choice rather than a deficit.

Finally, teaching about the broader context of generative AI, including its ethical, environmental, and social implications, creates space for students to explore their concerns. Supporting critical engagement in this way enables all students to make informed, reflective decisions about whether and how they wish to engage with AI tools as part of their learning.

6. Programme-Level Checklist: AI-Integrated Programme Design

This checklist is intended to support programme teams as they review, refresh, or redesign their curriculum in light of generative AI technologies. It poses a series of questions that encourage reflection upon the principles, strategies, and examples presented within this paper.

1. Purpose and Progression

- Have we reviewed programme learning outcomes for opportunities to embed AI literacy or align with digital graduate attributes?
- Are students supported to progress from basic to critical use of AI across the years of study?
- Have we aligned AI-enhanced tasks and assessments to different levels of Bloom's taxonomy?

2. Designing the Learning Environment

- Have we protected time and space for discussion, feedback, and collaboration?
- Are we actively designing learning opportunities that AI cannot replace, for example peer work, dialogic teaching, reflective engagement?
- Do students understand the value of these human elements in a tech-enabled learning environment?

3. Ethical Use and Acceptable Practice

- Is there a clear, shared framework (for example, a 'traffic-light' model) applied to every summative assessment?
- Are students taught when AI may be used in preparation - even if not in submission?
- Where AI is prohibited, have we designed conditions that make this meaningful (for example, Vivas, in-class work)?
- Have we established clear guidance on citing AI use, including tools like Grammarly or Overleaf?
- Are students introduced to the ethical, social, and environmental implications of generative AI, including how to use it in a responsible and sustainable way?

4. Respecting the Discipline: AI Use in Context

- Have we explored how generative AI aligns, or conflicts, with disciplinary ways of thinking or our values as a subject area?

- Are students given opportunities to compare AI-generated outputs to academic or professional standards in our field?
- Have we provided examples where AI use is pedagogically valuable, and where it's pedagogically limiting?

5. Digital and AI Literacy

- Are there scaffolded opportunities across the programme to develop AI-related skills?
- Do students know which tools are free, supported, and appropriate for use in our context?
- Have we acknowledged and addressed differences in access and prior experience?

6. Assessment Design

- Have we reviewed assessments for over-reliance on formats vulnerable to AI automation?
- Are we experimenting with new formats (for example, flipped assessment, critique, meta-analysis) to assess deeper learning?
- Is assessment varied, inclusive, and aligned with programme-level principles around AI use?
- Does the programme include Assured Credits or equivalent secured assessments to ensure a baseline of unaided student achievement, alongside opportunities for open and exploratory AI use?
- Have marking schemes been reviewed to reflect permitted AI use, including expectations for documentation, critical engagement, and citation where required?

7. Supporting Students

- Are students supported in their independent use of generative AI, including how to use it responsibly outside of taught sessions?
- Do we treat AI literacy as a skill to be revisited and extended across the programme?
- Are we actively working to reduce inequities in tool access, confidence, and support?
- Do we support students who choose not to use AI through clear design, balanced expectations, and reassurance that non-use is a valid academic choice?

7. Conclusion

The integration of generative AI into higher education is not a one-time activity, but an ongoing pedagogical and strategic consideration that must evolve alongside technological, institutional, and disciplinary developments. This paper has presented a programme-level approach to embedding generative AI across learning, teaching, assessment, and student support, with a particular emphasis on the mathematical sciences.

We have argued that generative AI cannot be introduced in a piecemeal or opportunistic manner. Its use must be aligned with programme outcomes, assessment strategy, disciplinary identity, and the wider student learning journey. Designing for AI requires intentionality, not only in identifying where its use is permitted, but in articulating how it supports learning and what forms of engagement are educationally meaningful.

When used thoughtfully, generative AI can enhance student confidence, foster independence, and support deeper forms of reflection and enquiry. But this potential is only realised when its use is transparent, principled, and scaffolded. Programme teams must protect what matters most in human learning, dialogue, collaboration, criticality, and intellectual struggle, while helping students develop the literacy, ethics, and confidence to use AI responsibly across varied contexts.

A programme designed for learning with generative AI is not one that integrates it everywhere. It is one that uses it purposefully, to extend thinking, to enrich engagement, and to prepare students for a world in which human and machine intelligence operate in partnership. As tools evolve, so too must our approaches to curriculum, assessment, and support. There is no single blueprint. But there is a shared responsibility, to ensure our programmes are coherent, inclusive, and future-facing.

The checklist within section 6 offers a practical tool for programme teams. It is designed to prompt discussion, guide planning, and support continuous reflection as institutions navigate the opportunities and challenges of learning with generative AI.

8. References

- Anderson, L. W. & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives: complete edition*. Addison Wesley Longman, Inc.
- Freeman, J. (2025). *Student Generative AI Survey 2025*. Technical report, Higher Education Policy Institute (HEPI), <https://www.hepi.ac.uk/2025/02/26/student-generative-ai-survey-2025>.
- Grove, M.J. (2024). Generative AI technologies and their role within assessment design. *Education in Practice*. Vol.5, Issue 1, pp 15 – 35. Available at <https://www.birmingham.ac.uk/documents/hefi/gai/eip-gai-and-assessment-design-publisher-version-august-2024.pdf>.
- Sabzalieva, E. & Valentini, A. (2023). *ChatGPT and artificial intelligence in higher education: Quick start guide*. UNESCO. Available at <https://unesdoc.unesco.org/ark:/48223/pf0000385146>
- Sharples, M. (2023). Towards social generative AI for education: theory, practices and ethics. *Learning: Research and Practice*, 9(2), 159-167.
- Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., Šigut, P. & Waddington, L. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, 19(1), 26. <https://doi.org/10.1007/s40979-023-00146-z>.

RESEARCH ARTICLE

The effect of Advanced Higher Mathematics on success within STEM degree-programs

Nathan Burns, Mathematics & Statistics Department, University of Strathclyde, UK.

Email: <mailto:nathan.burns@strath.ac.uk>

David Young, Mathematics & Statistics Department, University of Strathclyde, UK.

Email: <mailto:david.young@strath.ac.uk>

Louise Kelly, Mathematics & Statistics Department, University of Strathclyde, UK.

Email: <mailto:louise.kelly@strath.ac.uk%20>

Abstract

To gain access to higher education degree programmes, Scottish domiciled students must obtain the relevant grades in Scottish Higher qualifications typically achieved in either of the final two years of secondary school (S5 and S6). However, for admission to some of the most competitive degree programmes at higher education institutions in the UK, Advanced Highers are sometimes required or recommended. However, there exists little published literature on the effect of Advanced Higher on students' chances of success in higher education. This is relevant given that Advanced Highers are not compulsory and may not be available to every Scottish learner. This study fits Modified Poisson regression models to 10 years' worth of student registration records at a single Scottish higher education institution. Results indicated that students on Mathematics and Statistics programmes and had an Advanced Higher in Mathematics were 36.1% more likely to progress at the end of their first year and 57.3% to complete their degree within four years, compared to their peers with just Higher Mathematics. For other Science and Engineering programmes, there was a significant interaction between having a Higher/Advanced Higher Mathematics qualification and whether or not it was recommended. Given these results, if access to Advanced Highers is found to be associated with socio-economic background, then this could undermine Scotland's Widening Access agenda.

Keywords: Advanced Higher Mathematics, Student success, STEM degree programmes

1. Background

To gain access to higher education degree programmes, Scottish domiciled students must obtain the relevant grades in Scottish Higher qualifications typically achieved in the final two years of secondary school (S5 and S6). However, for S6 students who have already obtained a Higher in a given subject but wish to study further, the opportunity exists to sit a more advanced qualification, the Advanced Higher.

Advanced Highers were introduced in 1999 as a replacement for Certificate of Sixth Year Studies (Johnson and Hayward, 2008). Students may take Advanced Highers in a range of subjects, for example, English, Mathematics, Statistics, Physics, Chemistry, Biology, etc. (Scottish Qualifications Authority, n.d.). Typically, students are expected to have at least passed the relevant Higher as a pre-requisite to sitting an Advanced Higher, though ultimately presentation for the award is at the discretion of the school. Advanced Higher learners are encouraged to be more "pro-active" and "independent" in their studies to bridge the gap between secondary and higher education (Scottish Qualifications Authority, 2009). Advanced Highers rank as Level 7 on the Scottish Credit and Qualifications Framework (roughly equivalent to UK Level 4), the same level as a Higher National Certificate achieved at college (Scottish Credit and Qualifications Framework, 2023).

Unlike Highers, Advanced Highers are not compulsory subjects for university entry. Yet, for admission to some of the most competitive degree programmes at higher education institutions in the UK, Advanced Highers are sometimes required or recommended. For example, the University of Oxford expects pupils to achieve at least AAB at Advanced Higher unless there is sufficient evidence from the applicant that their school was unable to provide these qualifications (University of Oxford, n.d.). In contrast, the Universities of Glasgow and Edinburgh do not require Advanced Highers for most programmes except medicine (University of Edinburgh, 2023; University of Glasgow, 2023). The University of Strathclyde generally recommends, but does not require, Advanced Highers for entry to its Science, Engineering, Business and Law degrees (University of Strathclyde, 2024). In some Scottish institutions, students with Advanced Higher qualifications may be able to forgo certain examinations from the first year of their degree programme or skip the first year entirely and enter directly into second year. This is because the content from an Advanced Higher may overlap with the content taught at the first stage of the typical four-year Scottish degree programme.

A critical question arises from this context. If Advanced Highers are recommended, is this because they improve Scottish students' chances of success at university? In one of the few published literature that covers this topic, Croxford et al. (2014) found that students with "more Advanced Highers and/or A-levels achieve better degree outcomes on average". In 2018, students who had attended Glasgow Caledonian's "Advanced Higher Hub" associated their positive early-experience of university with attendance at the hub (MacFarlane, 2018). However, participants were self-selected, meaning that the results from MacFarlane (2018) are not generalisable.

If Advanced Highers do indeed improve Scottish students' chances of success at university, it then begs the question of whether or not Scottish students have equal access to Advanced Highers in secondary school. This question has been raised by various British media outlets (Borland, 2023; The Herald, 2018). Some have even referred to what they perceive as unequal access to Advanced Highers as a "postcode lottery" (Phipps, 2018). This coverage serves to highlight the public interest in access to Advanced Highers and their impact on educational outcomes.

The aim of this paper is to contribute to the literature on Advanced Highers and their effect on student's academic outcomes at higher education. Using university registration data for students from Science and Engineering programmes, the following research question will be answered:

Does Advanced Higher Mathematics improve students' chances of achieving a positive outcome in Mathematics, Science and Engineering degree programmes?

It was decided to focus on Mathematics since this is one of the most commonly recommended Advanced Highers across a range of Science and Engineering programmes. If Advanced Higher Mathematics is found to have positive effect on student's academic outcomes at university and future analyses find that access to Advanced Highers is not equal, then this could be problematic.

2. Data

The data for this analysis came from the University of Strathclyde's school-leavers dataset (SLD). These were the same data analysed in Burns et al. (2025), hence many of the definitions in the SLD remain the same across both analyses. The SLD is a combination of student registration and attainment data, entry requirements data and the Scottish Index of Multiple Deprivation (SIMD) datasets (Scottish Government, 2016, n.d.). SIMD is a commonly-used measure of area-level deprivation across Scotland, where SIMD Quintile 1 represents the 20% most deprived areas and SIMD Quintile 5 represents the 20% least deprived areas. For more information on SIMD see (Scottish Government, 2020). The SLD only considers "Scottish school-leavers", defined to be full-

time, first-degree, Scottish domiciled undergraduates, who were aged 18 or under at the point of their first registration. For this analysis the SLD was subset to only include students from the Faculties of Science and Engineering. The resultant subset was denoted the “STEM-SLD” and contained 6,914 unique students who each began their registration at the University between academic sessions 2012/13 and 2018/19 (Table 1).

2.1. Defining the Progression and Completion Outcomes

There were two binary academic outcomes of interest: progression at the end of the first registration year (Progression) and completion of a Bachelor’s with Honours degree within four years (Completion). These definitions are identical to those defined in Burns et al. (2025).

Students were considered to have successfully progressed if they advanced one academic stage after their first year of registration. Students who failed to progress may have been withdrawn, have been in suspension (for academic or personal reasons) or may have repeated a stage of their programme. Around 89.5% of students in the STEM-SLD successfully progressed at the end of first year (Table 1).

Bachelor’s with Honours degrees are typically four years’ duration in Scotland. Thus, students were considered to have successfully completed their degree if they had achieved a: first-class, second-class, or third-class honours degree, or had passed the fourth stage of their Integrated Master’s programme, within four registration years (regardless of whether they changed degree programme). Integrated Master’s students were included in the analysis because (i) they could not be distinguished from Bachelor’s with Honours students, and (ii) various programmes which offered these pathways were identical up to the final Masters year. Failure to complete a degree included anyone who exited the university at any stage with none of the aforementioned classifications or took longer than four years to complete their degree. Roughly 71.1% of students from Academic Cohorts 2012/13 – 2018/19 successfully completed their degree within four years (Table 1).

Table 1: Summary of categorical and outcome variables within STEM-SLD dataset (began registration between 2012/13 – 2018/19).

		Count	Proportion
Categorical Variables			
Academic Cohort	2012/13	1013	0.147
	2013/14	1040	0.150
	2014/15	1044	0.151
	2015/16	1000	0.145
	2016/17	967	0.140
	2017/18	943	0.136
	2018/19	907	0.131
Best Mathematics Qualification	Adv. Higher	3397	0.491
	Higher	3474	0.502
	None	43	0.006
Department	Mathematics and Statistics	760	0.110
	Other	6154	0.890

Ethnicity	Ethnic-minority	560	0.081
	Refused/Not given	47	0.007
	White	6307	0.912
SIMD Quintile	1	682	0.099
	2	932	0.135
	3	1199	0.173
	4	1545	0.223
	5	2556	0.370
Sex	Female	2200	0.318
	Male	4714	0.682
Outcome Variables			
Progression	No	723	0.105
	Yes	6191	0.895
Completion	No	1996	0.289
	Yes	4918	0.711
Total	-	6914	1.00

2.2. Prior Attainment and Best Mathematics Qualification

Each student's "Prior Attainment Points" from secondary school was defined as the combined "score" they had achieved across their Higher and Advanced Higher qualifications. A simple scoring system was used such that for Higher the grades: A – 3 points, B – 2 points, C – 1 point, D – 0 points; while for Advanced Higher: A – 4 points, B – 3 points, C – 2 points and D – 1 point. A similar definition for prior attainment was also used in Burns et al. (2025). A single point increase corresponds to an increase in grade in Higher or Advanced Higher, for example a C to a B, or a B to an A. The Prior Attainment Points can therefore be interpreted as each of the Scottish students' academic potential at the moment they first registered at the university. UCAS tariff points were considered but ruled-out in favour of Prior Attainment Points since a single-point increase was easier to interpret. The median Prior Attainment Points total across the STEM-SLD was 19.00 points, which is roughly the equivalent of six Higher A grades.

The Best Mathematics Qualification is an identifier variable that indicates whether the student had ever received an A-D grade at Advanced Higher Mathematics. Those who failed Advanced Higher Mathematics but had the equivalent Higher were classified as "Higher". Those who had neither of these qualifications were classified as "None" (43 students). These students came predominantly from the departments of Pharmacy, Architecture and Computing Science. It is likely the case that these students either had an alternative Mathematics qualification that was recognised by the department (e.g. A-level), or that Mathematics was not a required subject when the student applied. It was assumed that any passing grade at Advanced Higher is equivalent to, or better than, any grade awarded at Higher. The Department of Mathematics and Statistics had the largest proportion of Advanced Higher Mathematics students at 76.8%. The remaining departments had a proportion which ranged from 14.8% (Strathclyde Institute of Pharmacy and Biomedical Sciences) to 75.9% (Mechanical and Aerospace Engineering). The median Prior Attainment Points total for Advanced Higher Mathematics students was 21.00 points and for Higher Mathematics students was 16.00 points.

2.3. Recommendation of Advanced Higher Mathematics

For this analysis, if a degree programme had ever explicitly encouraged the study Advanced Higher in the University's 2012/13 – 2021/22 hand-outs to prospective undergraduates, it was considered to have recommended it. Advanced Higher Mathematics is recommended to all students studying a degree programme offered by the Mathematics and Statistics department. Across the "other" Science and Engineering departments this recommendation varied from programme-to-programme. Within other Science and Engineering programmes which recommended Advanced Higher Mathematics, 58.7% of students held this qualification. In programmes which did not recommend Advanced Higher Mathematics, only 24.4% of students held this qualification.

Breaking this down further, there were higher progression and completion rates within Advanced Higher Mathematics students when compared to Higher Mathematics students (Figure 1); this was regardless of whether or not Advanced Higher was recommended. It is notable that progression/completion rates for Advanced Higher Mathematics students were relatively similar whether or not the qualification was recommended (Figure 1). For Higher Mathematics students on the other hand, completion rates on programmes which recommended Advanced Higher were 9.2 percentage-points lower than on programmes which did not recommend it (Figure 1). The number of students that had neither a Higher nor Advanced Higher Mathematics qualification was too small to interpret any valid conclusions on their progression and completion rates.

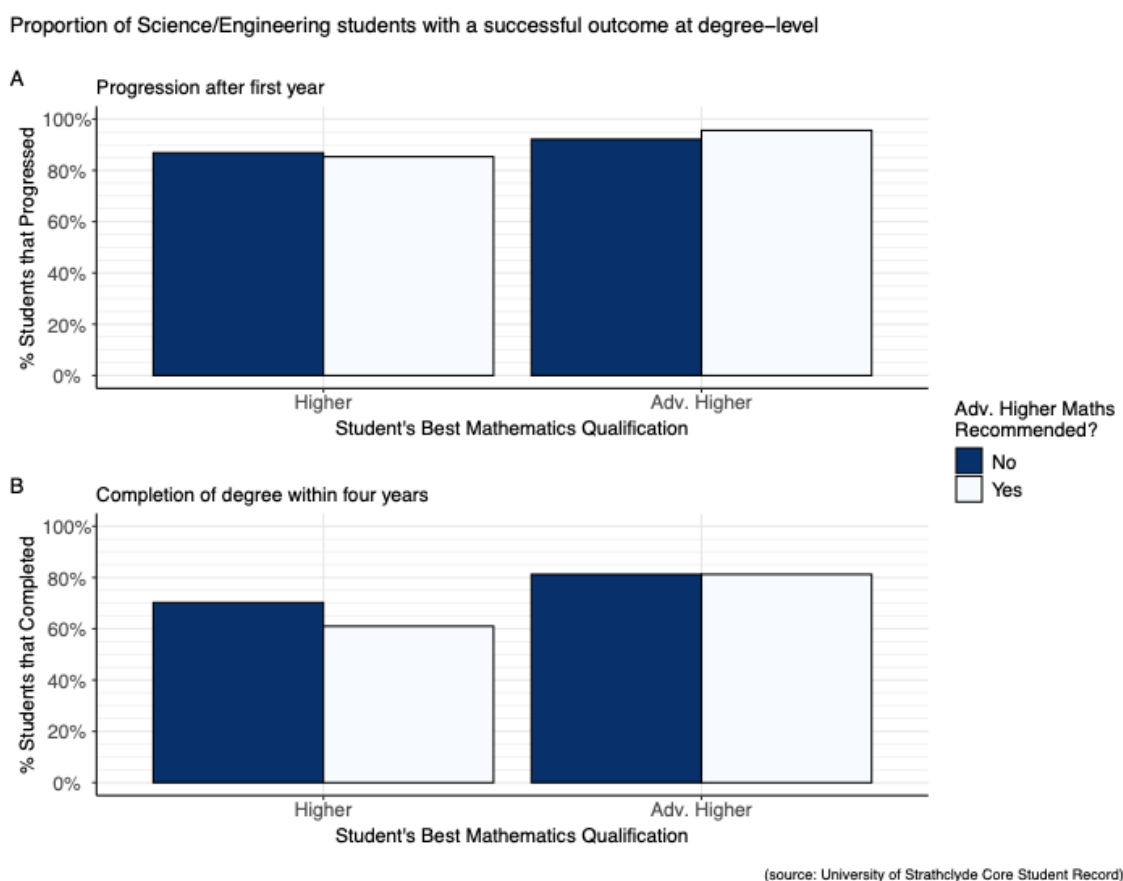


Figure 1: The proportion of successful progressions/completions amongst students in other Science and Engineering programmes (not including Mathematics), grouped by their Best Mathematics Qualification and whether or not their programme recommended Advanced Higher Mathematics.

3. Methods

Just as in Burns et al. (2025), Poisson regression models were fit to the data given that they can appropriately model the binary outcomes of progression and completion (random variable Y) when the error terms are calculated using “sandwich estimation” (Zeileis, 2006). Such models are known as modified Poisson regression models. Once exponentiated, the coefficients of these models approximate estimates of risk-ratios (RRs)

$$RR = \frac{P(Y = 1|X = 1)}{P(Y = 1|X = 0)} = \frac{\pi_1}{\pi_0}$$

where π_1 is the probability of experiencing the outcome for those who are exposed to the outcome, $X = 1$, over the probability π_0 of experiencing the outcome for those who were not exposed to the outcome, $X = 0$.

Two pairs of modified Poisson regression models were fit to subsets of the STEM-SLD dataset. The first pair of models looked at the progression and completion rates of students who were registered with the Department of Mathematics and Statistics only ($n = 760$), while controlling for the effects of Academic Cohort, Sex, Ethnicity and SIMD Quintile. The second pair of models used the same outcomes and control variables but for students registered with the rest of the Science and Engineering programmes offered by the University of Strathclyde ($n = 6,154$). The second pair of models also considered an interaction term between students' Best Mathematics Qualification, and whether or not their programme recommended Advanced Higher Mathematics, since not all programmes did so. Students who had neither a Higher nor Advanced Higher Mathematics qualification had to be removed to allow for this interaction term in model fitting (due to small sample sizes within groups).

4. Results

4.1. Department of Mathematics and Statistics

Students from the Department of Mathematics and Statistics who held an Advanced Higher Mathematics qualification were 37.4% [95% CI: 22.2%, 54.4%] more likely to progress and 57.9% [95% CI: 25.2%, 99.0%] more likely to complete their degree compared to their peers with only Higher Mathematics (Table 3). For each additional point (or grade) increase over the mean Prior Attainment Points, a student was 1.6% [95% CI: 0.9%, 2.3%] more likely to progress at the end of first year, and 5.9% [95% CI: 4.4%, 7.4%] more likely complete their degree within four years. There appears to be some association between the progression and completion rates of Mathematics and Statistics students and which Academic Cohort they belonged to. However, given that the sizes of these cohorts are relatively small (around 100 students each year) some volatility between cohorts is expected. Ethnic-minority students were 11.1% [95% CI: 1.8%, 21.3%] more likely to progress than White students, however both groups were just as likely to complete their degree. There does not appear to be an association between the academic outcomes and Sex and SIMD Quintile, in contrast to the findings from Burns et al. (2025).

4.2. Other Science and Engineering Departments

For each additional point (or grade) increase over the mean Prior Attainment Points, students from other Science and Engineering departments were 1.0% [95% CI: 0.8%, 1.2%] more likely to progress at the end of first year. There is no association between progression and any of the other explanatory variables in the model, except perhaps a small difference in the progression rates of those from Academic Cohorts 2012/13 and 2013/14.

Similarly, for each additional point (or grade) increase over the mean Prior Attainment Points, students from other Science and Engineering departments were 3.0% [95% CI: 2.6%, 3.4%] more likely to complete their degree within four years. Students on programmes which recommended Advanced Higher Mathematics were 13.9% [95% CI: 9.6%, 18.1%] less likely to complete their degree compared to students on programmes which did not recommend it. There was a significant interaction between Best Mathematics Qualification and whether or not Advanced Higher Mathematics was recommended. This means that the association between completion and holding an Advanced Higher Mathematics qualification was greater on programmes where it was recommended than courses where it was not. Students from SIMD Quintile 5 were 14.4% [95% CI: 7.1%, 22.1%] more likely to complete their degree than students from SIMD Quintile 1. Females were also 4.0% [95% CI: 0.7%, 7.4%] more likely to complete their degree than males.

Table 2: Risk-Ratio Estimates from the modified Poisson Regression model fit to student data from the Department of Mathematics and Statistics (n = 760).

Variables	Risk-Ratios	
	Progression Year 1 to Year 2	Completion of a Degree Prog.
(Intercept)	0.688 (0.588,0.806) [***]	0.413 (0.310,0.552) [***]
Best Maths Qual. – Adv. Higher (vs Higher)	1.374 (1.222,1.544) [***]	1.579 (1.252,1.990) [***]
Prior Attainment Points	1.016 (1.009,1.023) [***]	1.059 (1.044,1.074) [***]
2013/14 Cohort (vs 2012/13)	0.990 (0.916,1.070)	0.870 (0.717,1.056)
2014/15 Cohort (vs 2012/13)	0.941 (0.859,1.030)	0.748 (0.604,0.927) [**]
2015/16 Cohort (vs 2012/13)	0.886 (0.795,0.987) [*]	0.615 (0.466,0.813) [***]
2016/17 Cohort (vs 2012/13)	0.879 (0.792,0.975) [*]	0.816 (0.671,0.993) [*]
2017/18 (Cohort vs 2012/13)	0.871 (0.797,0.953) [**]	0.880 (0.739,1.048)
2018/19 Cohort (vs 2012/13)	0.878 (0.799,0.965) [**]	0.889 (0.741,1.067)
Female (vs Male)	0.984 (0.930,1.041)	1.053 (0.940,1.180)
SIMD Quintile 2 (vs 1)	1.027 (0.909,1.161)	1.029 (0.821,1.291)
SIMD Quintile 3 (vs 1)	1.043 (0.929,1.171)	1.101 (0.886,1.367)
SIMD Quintile 4 (vs 1)	1.019 (0.909,1.143)	1.065 (0.864,1.312)
SIMD Quintile 5 (vs 1)	1.087 (0.971,1.216)	1.088 (0.887,1.333)
Ethnic-minority (vs White)	1.111 (1.018,1.213) [*]	1.032 (0.846,1.258)
Refused/Not given (vs White)	0.810 (0.496,1.322)	0.613 (0.213,1.759)

Table 3: Risk-Ratio Estimates from the modified Poisson Regression model fit to student data from the rest of the Science and Engineering programmes (n = 6,154).

Variables	Risk-Ratios	
	Progression Year 1 to Year 2	Completion of a Degree Prog.
(Intercept)	0.874 (0.837,0.913) [***]	0.663 (0.612,0.718) [***]
Best Maths Qual. – Adv. Higher (vs Higher)	1.024 (0.993,1.056)	1.040 (0.988,1.094)
Prog. Recommended Adv. Higher Maths (vs not)	0.978 (0.952,1.005)	0.861 (0.819,0.904) [***]
Prior Attainment Points	1.010 (1.008,1.012) [***]	1.030 (1.026,1.034) [***]
2013/14 Cohort (vs 2012/13)	1.032 (1.003,1.062) [*]	0.996 (0.938,1.057)
2014/15 Cohort (vs 2012/13)	1.003 (0.973,1.033)	1.029 (0.972,1.089)
2015/16 Cohort (vs 2012/13)	0.985 (0.955,1.017)	0.994 (0.938,1.053)
2016/17 Cohort (vs 2012/13)	0.976 (0.944,1.008)	1.012 (0.955,1.072)
2017/18 Cohort (vs 2012/13)	0.997 (0.965,1.029)	1.057 (0.999,1.119)
2018/19 Cohort (vs 2012/13)	0.970 (0.938,1.003)	1.038 (0.980,1.099)
Female (vs Male)	1.008 (0.990,1.026)	1.040 (1.007,1.074) [*]
SIMD Quintile 2 (vs 1)	1.001 (0.960,1.043)	1.082 (1.003,1.167) [*]
SIMD Quintile 3 (vs 1)	1.014 (0.976,1.053)	1.083 (1.008,1.164) [*]
SIMD Quintile 4 (vs 1)	1.034 (0.998,1.072)	1.100 (1.026,1.178) [**]
SIMD Quintile 5 (vs 1)	1.026 (0.991,1.062)	1.144 (1.071,1.221) [***]
Ethnic-minority (vs White)	1.020 (0.991,1.049)	1.021 (0.967,1.077)
Refused/Not given (vs White)	0.922 (0.809,1.052)	0.841 (0.672,1.052)
Interaction: Best Maths Qual. & Recommended	1.035 (0.997,1.075)	1.083 (1.014,1.157) [*]

5. Discussion

The results indicate that Advanced Higher Mathematics had a strong and positive association with the successful progression and completion rates of students enrolled on Mathematics and Statistics degrees at the University of Strathclyde. The association between success and Advanced Higher Mathematics across other Science and Engineering programmes was more complicated to interpret. Programmes which recommended Advanced Higher Mathematics had lower completion rates than programmes which did not. However, this association was weaker if the student held an Advanced Higher Mathematics qualification. This could be seen as either a justification or, more cynically, a rationalisation for recommending Advanced Higher Mathematics in such programmes. Attainment in other subjects may be affecting the interpretation of the effect of Advanced Higher Mathematics. For example, this analysis did not account for the effects of other Advanced Highers in relevant science subjects, Physics, Chemistry, Biology, etc.

As acknowledged in Burns et al. (2025), Prior Attainment Points are also an imperfect measure of the academic potential to succeed though are simple to implement and interpret. Models were also fit using UCAS tariff points where the relationships between the covariates and the outcomes remained the same, including significance tests. Further investigation is required into how best to measure and compare similar attainment profiles across Highers and Advanced Highers.

Progression and degree completion are popular in the literature but are not ideal for fitting regression models given that they are not rare (<10%). A more effective approach may be the application of survival models such as those which measure the rate of student drop-out over time (Arulampalam et al., 2004). The models for the completion outcome do not include any information on students' attainment at university-level, which is assumed to be a critical explanatory variable. Future research should investigate whether this link is present across other Advanced Higher subjects and degree programmes and other higher education institutions.

The positive effect of Advanced Higher Mathematics on degree-level outcomes leads to the inevitable question of who has access to these qualifications. If access is not equal for all learners across Scotland, then this could be evidence of an unfair system. If students from more socio-economically deprived areas are disproportionately affected, then this could jeopardise Scotland's Widening Access ambitions. Further research should therefore establish whether there is a link between a student's socio-economic status and access to Advanced Higher.

6. References

- Arulampalam, W., Naylor, R.A., Smith, J.P., 2004. A Hazard Model of the Probability of Medical School Drop-out in the UK. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 167, 157–178.
- Borland, B., 2023. More than one in 10 schools no longer offer Advanced Higher England and Maths [WWW Document]. *Scottish Daily Express*. URL <https://www.scottishdailyexpress.co.uk/news/scottish-news/more-one-10-scots-schools-29536024> (accessed 2.1.24).
- Burns, N.P., Young, D., Sherriff, A., Black, P., Blackshaw, A., Kelly, L., 2025. Tracking the Success of Contextual Offer Students at One Scottish Higher Education Institution. *Higher Education Quarterly* 79, e70011. <https://doi.org/10.1111/hequ.70011>

Croxford, L., Docherty, G., Gaukroger, R., Hood, K., 2014. Widening Participation at the University of Edinburgh: Contextual Admissions, Retention, and Degree Outcomes. *Scottish Affairs* 23, 192–216. <https://doi.org/10.3366/scot.2014.0017>

Johnson, J., Hayward, D.G., 2008. *Scottish Highers and Advanced Highers*.

MacFarlane, K., 2018. *An Evaluation of the Advanced Higher Hub: The Learner Perspective*.

Phipps, S., 2018. 'Postcode lottery' of Scotland's Advanced Highers [WWW Document]. SecEd. URL <https://www.sec-ed.co.uk/content/news/postcode-lottery-of-scotland-s-advanced-highers/> (accessed 2.12.24).

R Core Team, 2023. *R: A Language and Environment for Statistical Computing*.

Scottish Credit and Qualifications Framework, 2023. *Interactive Framework* [WWW Document]. Scottish Credit and Qualifications Framework. URL <https://scqf.org.uk/about-the-framework/interactive-framework/> (accessed 11.2.23).

Scottish Government, 2020. *Scottish Index of Multiple Deprivation 2020: introduction* [WWW Document]. URL <http://www.gov.scot/publications/scottish-index-multiple-deprivation-2020/> (accessed 10.6.23).

Scottish Government, 2016. *Scottish Index of Multiple Deprivation 2016 - gov.scot* [WWW Document]. URL <https://webarchive.nrscotland.gov.uk/20190708060827/https://www2.gov.scot/Topics/Statistics/SIMD> (accessed 3.17.22).

Scottish Government, n.d. *Scottish Index of Multiple Deprivation (Historical) - 2004-2012* [WWW Document]. statistics.gov.scot. URL <https://statistics.gov.scot/data/scottish-index-of-multiple-deprivation-historical-i> (accessed 2.8.22).

Scottish Qualifications Authority, 2009. *Introducing Advanced Highers*.

Scottish Qualifications Authority, n.d. *A to Z of National Qualification (NQ) subjects* [WWW Document]. URL http://www.sqa.org.uk/sqa/CCC_FirstPage.jsp (accessed 2.21.24).

The Herald, 2018. *Warning over lack of access to Advanced Highers for poor pupils* [WWW Document]. The Herald. URL <https://www.heraldscotland.com/news/16218177.warning-lack-access-advanced-highers-poor-pupils/> (accessed 2.1.24).

University of Edinburgh, 2023. *Undergraduate Study 2024 Entry | SQA Highers and Advanced Highers* [WWW Document]. The University of Edinburgh. URL <https://www.ed.ac.uk/studying/undergraduate/entry-requirements/scottish-qualifications/highers> (accessed 2.15.24).

University of Glasgow, 2023. *University of Glasgow - Undergraduate study - Information about entry requirements - 2024 Admissions guidance* [WWW Document]. gla.ac.uk. URL <https://www.gla.ac.uk/undergraduate/entryrequirements/guidance/> (accessed 3.28.24).

University of Oxford, n.d. *Response to Scottish Qualifications Reform | University of Oxford* [WWW Document]. URL <https://www.ox.ac.uk/admissions/undergraduate/courses/entrance-requirements/response-scottish-qualifications-reform> (accessed 11.2.23).

Wickham H, Averick M, Bryan J, Chang W, McGowan LD, François R, Golemund G, Hayes A, Henry L, Hester J, Kuhn M, Pedersen TL, Miller E, Bache SM, Müller K, Ooms J, Robinson D, Seidel DP, Spinu V, Takahashi K, Vaughan D, Wilke C, Woo, K, Yutani H, Wickham H, Bryan J, Chang W, McGowan LD, François R, Golemund G, 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4, 1686. <https://doi.org/10.21105/joss.01686>

Zeileis, A., 2006. Object-Oriented Computation of Sandwich Estimators. *J. Stat. Soft.* 16, 1–16. <https://doi.org/10.18637/jss.v016.i09>

7. Appendix

Prior Attainment Points was mean-centred in the model fits. The p-values from Wald's tests on each coefficient were derived using $\alpha = 0.05$ as the critical value. All analyses were conducted using the statistical software R (version 4.3.1) (R Core Team, 2023). Poisson regression models were fit using the `glm()` function from the stats package (R Core Team, 2023). Robust variances for the modified Poisson Regression model were derived using the sandwich (3.1-0) package (Zeileis, 2006). Additional packages for general data cleaning and visualisations were used from the tidyverse (2.0.0) (Wickham H, Averick M, Bryan J, Chang W, McGowan LD, François R, Golemund G, et al., 2019).

THIS PAGE
DELIBERATELY
LEFT BLANK

RESEARCH ARTICLE

Student Perceptions of TabletPC Use in Mathematics Teaching, and Student Preferences of Different Delivery Modes

Alena Haddley, Department of Mathematical Sciences, University of Liverpool, Liverpool, UK.

Email: a.haddley@liverpool.ac.uk

Joel A. Haddley, Department of Mathematical Sciences, University of Liverpool, Liverpool, UK.

Email: j.a.haddley@liverpool.ac.uk

Abstract

Traditional mathematics education using a blackboard has, in recent decades, been complemented or replaced by emerging technologies. The pandemic was a notable catalyst for adoption of technology, as educators had no choice but to engage with technology so that learning and teaching could continue remotely. The present research was conducted at a large UK university which invested in TabletPCs to facilitate this remote education. The research verified that the benefits of TabletPCs described in the literature were indeed being achieved locally. The research further explored student perceptions and preferences of different lecture delivery modes, including TabletPCs and boards. The research was conducted before and after remote delivery to explore whether student opinions differed following this period of greater exposure to technology-driven education. The main result of the research is a student preference for multi-modal lecture delivery, which was slightly stronger in the post-pandemic survey. A further recommendation is for educators to consider the value of different tools and their individual advantages when planning teaching activities, rather than being led by a strong discipline culture.

Keywords: Mathematics Education, Lecture Delivery, TabletPC, Education Technology.

1. Introduction

The first modern blackboard was invented in 1801. Blackboard use proliferated following the 1870 Education Acts, which introduced free and compulsory education in England and Wales. The blackboard offered a solution to teaching at the larger scale that was now required. Manuals were soon produced that detailed the techniques – and etiquette – of effective teaching (Day, 1967; Wylie, 2012). Early articles describe how blackboards may have had an imposing presence in classrooms (Hester, 1902), and others advised on decorating the blackboard with images of seasonal flowers (Emerson, 1896). Blackboards are rarer in the present day, yet are still popular in higher education mathematics teaching as a suitable medium for the abstract reasoning of mathematics (Greiffenhagen, 2014). Indeed, studies have shown that some students prefer traditional ‘chalk and talk’ to static slides (Rudow and Finck, 2015). However, the TabletPC (a touchscreen laptop that accepts handwritten input) can recreate some of the advantages of a blackboard, due to live handwriting using a digital pen; and has further advantages of its own (Fister and McCarthy, 2008). A strong discipline culture is proposed as a reason for persistent belief that blackboards are the most suitable medium for mathematics teaching, and a reduction in use is partly due to necessity (e.g. available facilities or class sizes), and partly due to acceptance and adoption of new technologies (Billman et al., 2018). These factors have led to mathematics students experiencing a variety of delivery modes during their higher education studies. The authors ran a survey to explore students’ relative preferences of delivery modes during the academic year 2021-22, asking participants to consider experiences both prior to the fully remote delivery necessitated by the pandemic, and modes of delivery within the fully remote context. The fully remote year required educators to rapidly

adopt and develop their confidence with digital education tools (Myry et al., 2022), and students demonstrated increased expectation for digital delivery, or digital-supported delivery, following the fully remote year (Suleri, 2020). The authors repeated the survey post-pandemic, during the academic year 2022-23, focusing this time only on in-person delivery modes. This paper explores the comparative preferences of students pre-pandemic and post-pandemic; giving contemporary insight into preferences for delivery modes and exploring if this changed during the fully remote year.

2. Literature Review and Context

In this paper, we will focus on the development of Tablet PCs within education. Although educationally-focused Tablet PCs have been around since the late 1980s (Wiggins and Eglowstein, 2017), the technology advanced for mainstream educational use in the early part of the 21st century (Ellis-Behnke et al., 2003). In an early paper describing their use in mathematics education, Gorgievski et al (2005) surveyed the perceptions of calculus students of this emerging technology. Numerous benefits of Tablet PCs have since been reported.

- Handwritten notes can be produced in real-time during teaching. The notes can be shared with students (Fister and McCarthy, 2008). A video capture of the teaching session can be shared with students (Galligan et al., 2012). This approach is very compatible with 'gapped notes' (Sambrook and Rowley, 2010).
- The Tablet PC is a full PC system, making it straightforward to switch between applications. For example, software demonstration, video playback, website navigation, text highlighting (and so on) can all be achieved on the same device and will all be captured in the video recording of the lecture.
- In-person teaching can be improved through eye contact. As the Tablet PC can be connected to a projector from any angle, a lecturer can face students while teaching, rather than facing a board (Billman et al., 2018).
- Eliminating chalk dust enhances air quality in classrooms and removes any potential associated health risk (Lin et al., 2015; Majumdar and William, 2009). Eliminating the use of dry erase pens reduces the risk they will end up in landfills. It is difficult to find statistics for recycling rates of dry erase pens, but an estimated 19% of plastic in the UK ended up in landfills in 2020 (PlasticsEurope, 2022). It should be noted for balance that laptop production also has environmental impacts (Hoang et al., 2009).
- Remote interactions between educators and students can be improved using Tablet PCs as they provide a means for real-time whiteboard collaboration, mimicking in-person interactions (Kohorst and Cox, 2007).

Comparative studies have indeed demonstrated strong student satisfaction with the use of Tablet PCs for teaching (Maclaren et al., 2017).

The present research was conducted with participants studying on mathematics programmes in a large UK university. At this university, several mathematics lecturers were using Tablet PCs to lead or support teaching delivery prior to the pandemic. When it became apparent that teaching would continue under a national lockdown, the institution made a bulk purchase of Tablet PCs for all mathematics lecturers, aiming to enhance the quality and value of remote teaching. The delivery modes both pre-pandemic and post-pandemic were (and are) varied, and students have consistently been likely to experience a diversity in approaches across all modules. The authors identified the

following lecture delivery modes in the department. In all cases, 'handwritten' means live during the teaching session, and 'slides' means pre-prepared presentation files such as PDF or PowerPoint:

- Handwritten notes on a board.
- Slides displayed on a projector, with no handwritten notes or annotations.
- Slides displayed on a projector, with handwritten notes on a separate board.
- Handwritten notes using a Tablet PC, using a digital pen, displayed on a projector.
- Slides displayed on a projector using a Tablet PC, using a digital pen, with handwritten notes and slide annotations on the Tablet PC.

3. Methodology

The study was conducted by administering an anonymous online survey to student participants, which consisted of three sections:

1. Perceptions of TabletPC delivery. Participants responded against a five-point Likert scale to provide insight into perceptions around TabletPC delivery. This section was based on the questions of Gorgievski et al (2005), and was used to verify that the benefits of TabletPC delivery found in the literature were being achieved in the local context.
2. Ranking of delivery modes. Participants were asked to rank the five delivery modes stated above, with an aim to identify trends or broad preferences shared among students. The methodology and presentation of results was based on Maclaren et al (2017), but with delivery modes changed for our context.
3. Open ended question. This allowed participants to clarify views on TabletPC delivery and/or their ranking of delivery modes. Thematic analysis was performed on responses.

The survey was deployed twice: first during the year of remote teaching (Survey 1), and again when in-person teaching resumed (Survey 2). During remote teaching, all students had previously experienced TabletPC delivery, and so all students in the department were invited to participate in the survey, reflecting on their in-person experiences. When in-person teaching resumed, some students may not have taken modules that used TabletPC delivery. Instead of inviting all students in the department to act as participants, the invitation was narrowed to students registered on modules which used TabletPC delivery. Hence all participants in the survey had experienced TabletPC delivery.

4. Results

4.1. Perceptions of TabletPC Use

Survey 1 had $n_1=21$ responses (population ~1000) and Survey 2 had $n_2=66$ responses (population ~500). Comparative bar charts are shown for the questions in the first section of both surveys (Figures 1-4), about the effectiveness of TabletPCs. Detailed data can be found in the Appendix (Tables 1 and 2).

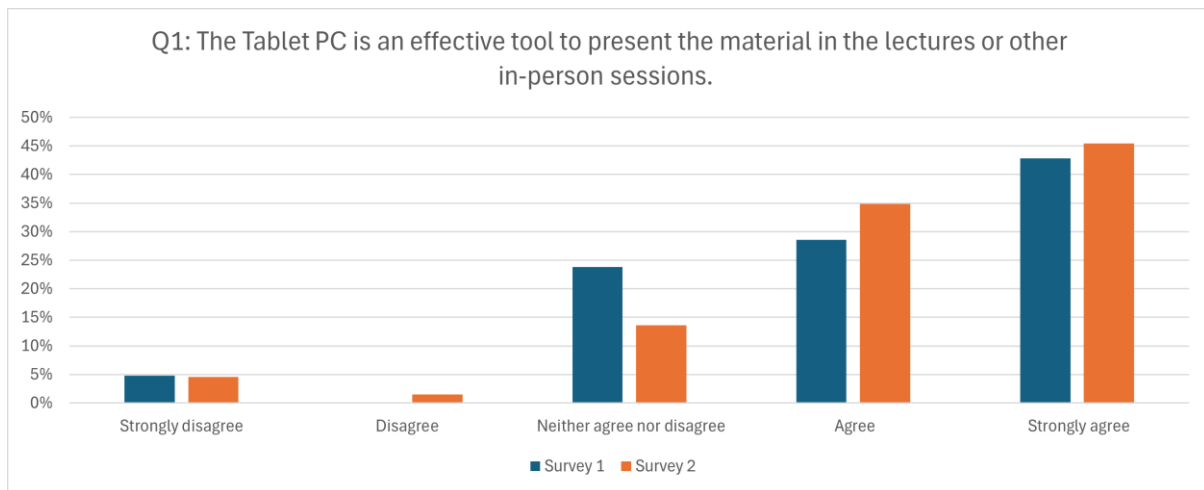


Figure 1: Breakdown of responses for Question 1 in Survey 1 and Survey 2

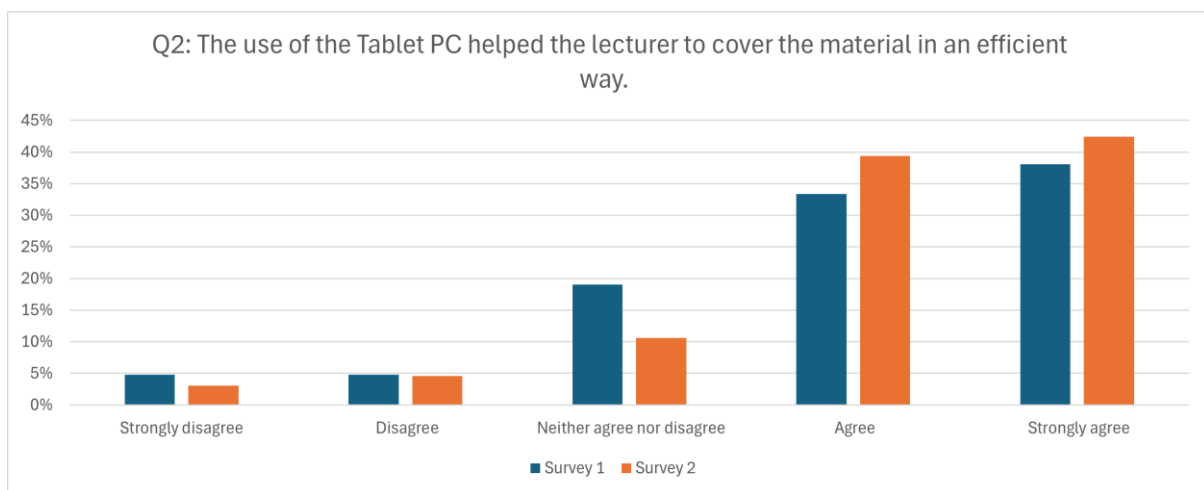


Figure 2: Breakdown of responses for Question 2 in Survey 1 and Survey 2

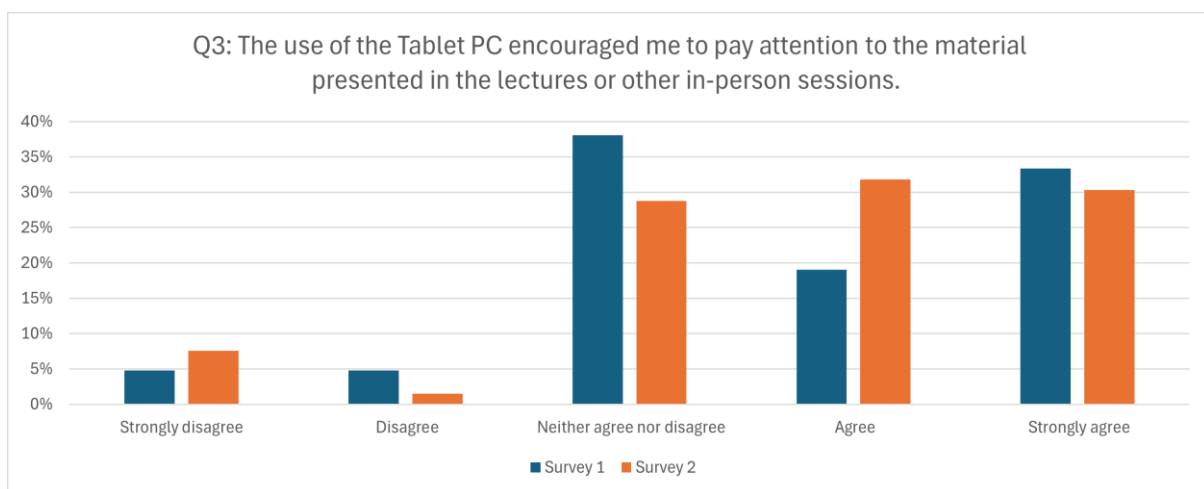


Figure 3: Breakdown of responses for Question 3 in Survey 1 and Survey 2

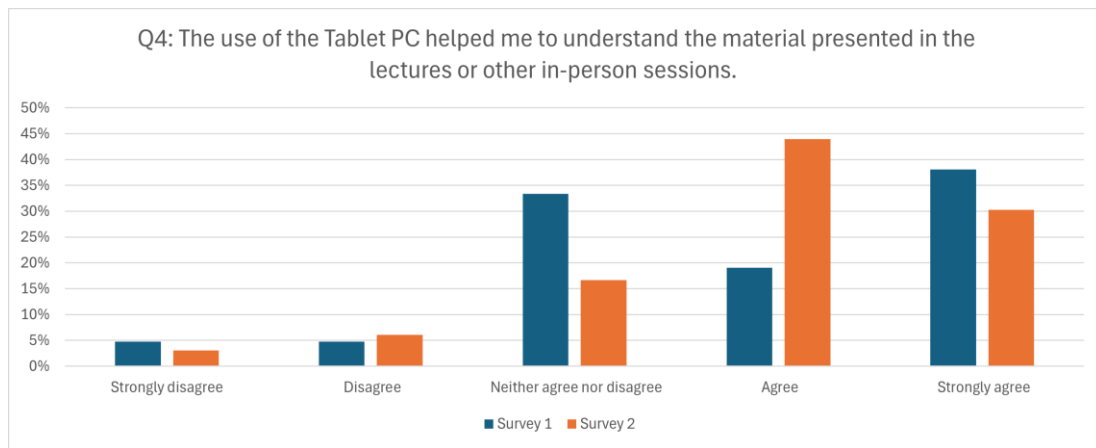


Figure 4: Breakdown of responses for Question 4 in Survey 1 and Survey 2

Each time the survey was deployed, a majority of participants responded with 'Agree' or 'Strongly Agree' for each question (although the majority for Q3 was narrow in Survey 1, due to a high neutral response). There was little change in the proportion of negative responses between the two surveys, and these responses were in the minority. Responses for Q1 and Q2 show a clear but slight positive trend. Q3 and Q4 in Survey 1 were bimodal, between 'Neutral' and 'Strongly Agree', but this polarisation was not seen in Survey 2: Q3 is more uniform at the positive end, and Q4 is unimodal with left skew towards positive.

4.2. Ranking Delivery Modes

Results are presented in diverging stacked percentile bar charts, with the vertical centre of neutral responses aligned (Figure 5). The order of the delivery modes on the questionnaire was presented as stated earlier, but the modes are ordered by preference in the chart: this turned out to be the same ordering for both deployments of the survey.

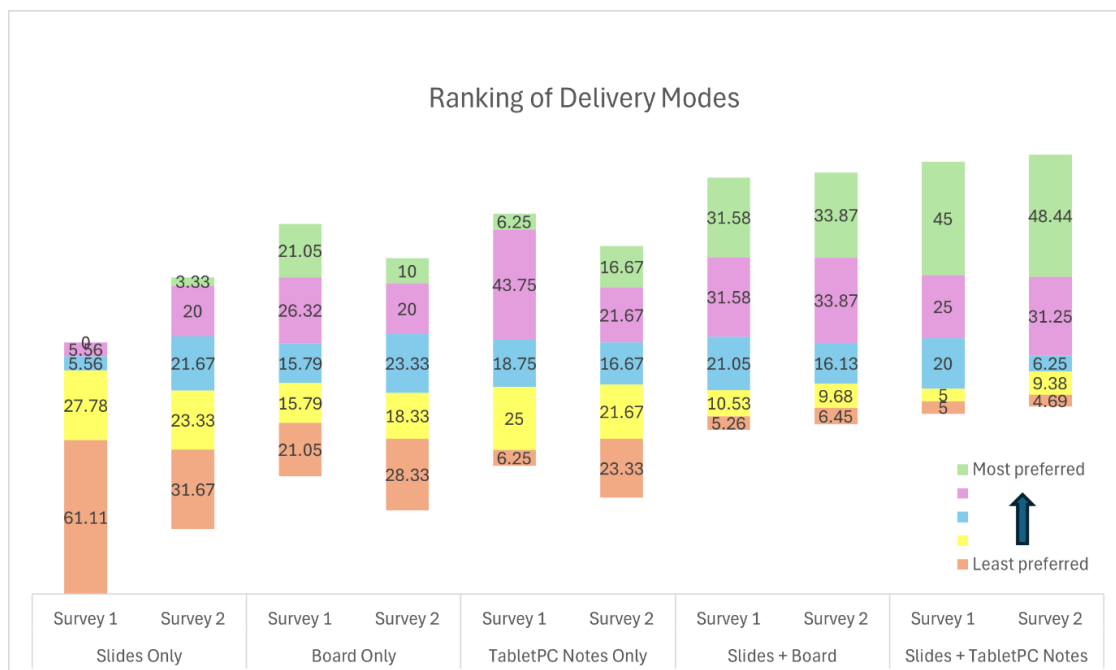


Figure 5: Diverging stacked percentile bar charts for ranking of delivery modes in Survey 1 and Survey 2

Survey 1 shows a notable negative perception of a slides-only approach relative to other delivery modes. It remained the most negatively perceived in Survey 2, but not as severely negative. The two 'notes-only approaches' were significantly less positively perceived in Survey 2 compared to Survey 1. The mixed modal approaches – slides and board, or slides and Tablet PC Notes – were consistently the most positively perceived delivery modes. Given these are relative perception scores (rankings), and the multi-modal approaches were almost constant between surveys, it appears the gap between 'slides only' and 'notes-only' approaches has narrowed; whereas the gap between 'unimodal' and 'mixed modal' approaches has widened.

4.3. Open Response Thematic Analysis

Out of $n_1=21$ responses for Survey 1, seven participants provided open responses; out of $n_2=66$ responses for Survey 2, 16 participants provided open responses. Identified themes follow:

Suitability for Online Context: Three responses in Survey 1 specifically praised TabletPCs in the remote teaching context, for providing increased clarity compared to capturing a board or notebook with a fixed camera. Although this was not asked, it is perhaps unsurprising that participants shared this as it was their most recent learning experience.

Multi-Modal Approaches and Engagement: In Survey 1, three responses reported that the mode is less important than how it is integrated into teaching, and combining approaches (i.e. a multi-modal approach) makes sessions more engaging, regardless of whether the live writing uses a TabletPC or a board. This was reinforced by five responses in Survey 2, which reported that multi-modal delivery made it easier to focus on learning during a teaching session, rather than focus on replicating notes delivered on the board. The live handwriting component was reported to be useful for understanding the material, and one response reported that the removal of the requirement to copy everything was inclusive practice, suitable for neurodiverse students (Boyle et al., 2015). It is noted that, although TabletPCs with annotation ranked higher than slides combined with writing on the board, the difference is not enough to draw a definitive conclusion about a common preference for one of them over the other.

Pace and Review: In Survey 2, six responses reported that the video and notes captured by the TabletPC provide an advantage for subsequent review of learning: something that is not always readily available for board capture at the institution. Of these respondents, 3 explained that this can compensate for faster-paced sessions, which risk being too fast if there is too much to write down.

Strong Blackboard Preference: In Survey 2, five responses strongly preferred boards, stating in categorical terms that it is the best delivery medium for mathematics. Three of these responses specifically mention blackboards. But even stronger than stating that it is currently the best medium, one response says it always has been ('a board and chalk has been used for thousands of years for mathematics'), and one response says it always will be ('nothing will ever beat chalk'). It is noted that four of these five respondents nevertheless stated their strongest preference was a multi-modal approach, involving slides and the board.

5. Discussion

5.1. Verifying results from the literature

Perceptions of TabletPCs in (Results Section 4.1) were mostly in line with the literature, except for a high neutral response for TabletPCs encouraging students to pay attention. Although this is not explained by thematic analysis of open responses, we hypothesise that it may be due to the novelty

wearing off. Literature from as early as 2013 (Schnackenberg, 2013) discussed how TabletPCs were prevalent in homes and workplaces, how adoption was growing within education, and how the devices could be effectively integrated into classrooms. A 2023 survey showed that almost half of all students own a tablet (UCAS, 2023).

5.2. Multi-Modal Delivery

Both Survey 1 and Survey 2 yielded the same overall ranking of preferred delivery modes, with multi-modal delivery rated higher than unimodal delivery. In Survey 1, the ranking within unimodal delivery modes had 'slides only' clearly earning the lowest ranking. In Survey 2, the gap was closed between 'slides only' and other unimodal delivery modes. This suggests that participants in Survey 2 were less discriminating between different unimodal delivery modes and had a stronger preference for mixed-modal delivery rather than strong preferences within these categories. This observed preference aligns with concepts of Cognitive Load Theory. Specifically, unimodal delivery modes are linked to the 'split attention effect' (Chandler and Sweller, 1992). This undesirable outcome occurs when learners are processing inputs that are not effectively integrated; for example, if information is presented on a slide and this information is also read to students, then this can trigger the split attention effect. Participants reported in open responses that the pace of unimodal delivery modes require relatively more effort from students to keep up: this means that student attention on replicating notes can detract from actively listening to and understanding the discussion, hence triggering the split attention effect. Conversely, the multi-modal delivery modes are linked to the 'mixed-modal effect' (Mousavi et al., 1995) in which cognitive load is reduced by having material presented in a mode complementary to the active delivery, meaning learners have immediate access to resources as needed, rather than taking up valuable space in working memory. It should be noted that the split attention effect and mixed modal effect occur based on how effectively information from different modes is integrated in the presentation and is not intrinsically linked to the modes surveyed; however, open responses suggest that the delivery modes are delivered in such a way as to link to these aspects of Cognitive Load Theory. The authors believe this to be practical evidence supporting the theoretical framework.

Participants also cited the inclusive practice of making resources available. All surveyed methods (dependent on the technology of the teaching space) afford the opportunity to record the audio and visual components of the teaching session. Only slides only, or multi-modal approaches, afford the opportunity to share some of these resources in advance of the session.

5.3. Discussing the claim that blackboard is best

It is not surprising, given results found elsewhere in the literature, that some respondents reported a strong preference for blackboard delivery. From the literature review, we know that blackboards have been integrated into mass education for around 150 years. It is unclear whether the participant is being figurative or literal when citing 'thousands of years,' but it is clear this is perceived to be the educational norm. Indeed, there is considerable advocacy for blackboards.

6. Conclusion and Recommendation

The surveys asked for student perceptions in a general sense, and did not consider the context of individual teaching activities. Some teaching activities might lend themselves more to one mode than another: e.g. student collaboration might be most effective on a large physical board, compared to a smaller TabletPC; conversely, software demonstration would be simple on a TabletPC but impossible on a board. The present study did not consider educator preferences and proficiencies, which are critical to ensuring benefits of a given mode are realised in practice. It would not be valid to conclude a particular mode as the definitive 'best,' especially as the preferred ranking was not

substantially different between the highest ranked modes. Having said that, the advantages of TabletPCs described in the literature were evidenced in the present research, and they are a suitable and effective tool for delivery of mathematics. The strong discipline culture might discourage some educators from considering them. This leads to the first recommendation.

Recommendation 1: Educators are recommended to consider the breadth of contemporary tools available, and their individual advantages, when determining the most appropriate delivery mode for a teaching activity.

The clearest preference arising from delivery mode rankings was for multi-modal approaches, which also aligns with Cognitive Load Theory.

Recommendation 2: Incorporate multi-modal delivery, combining dynamic presentation of delivery with complementary static presentation of information to reduce split attention effect arising from having to keep up with the pace.

In a similar vein, but also linked to inclusive practice, students reported that having resources in advance could support note-taking and active listening within the lecture.

Recommendation 3: Consider what resources may be provided in advance of the lecture, which can especially complement multi-modal delivery.

This paper concludes with a comment about the preference for blackboards, and the associated strong discipline culture. The authors were able to find sources which provided logical arguments supporting blackboard use, and socialised evidence supporting advantages such as speed, space, visibility and legibility (Greiffenhagen, 2014). Although such evidence is valid, the authors struggled to find direct evaluation of such advantages, and their implications for learning; either considering the medium independently, or comparatively against other media. Lew et al (2016) support the claim about lack of empirical evidence to support traditional mathematics instruction more generally, also demonstrating that what may traditionally be thought of as a good lecture may not have the intended learning value for students. The authors note an incongruity between the strength and breadth of the cultural preference for blackboard delivery, and a lack of empirical research to evidence its benefits.

7. Appendix

7.1. Survey 1 – breakdown of responses

1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Strongly agree

	1	2	3	4	5
The Tablet PC is an effective tool to present the material in the lectures or other in-person sessions.	1	0	5	6	9
The use of the Tablet PC helped the lecturer to cover the material in an efficient way.	1	1	4	7	8
The use of the Tablet PC encouraged me to pay attention to the material presented in the lectures or other in-person sessions.	1	1	8	4	7
The use of the Tablet PC helped me to understand the material presented in the lectures or other in-person sessions.	1	1	7	4	8

Table 1: Breakdown of responses for Survey 1

7.2. Survey 2 – breakdown of responses

1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Strongly agree

	1	2	3	4	5
The Tablet PC is an effective tool to present the material in the lectures or other in-person sessions.	3	1	9	23	30
The use of the Tablet PC helped the lecturer to cover the material in an efficient way.	2	3	7	26	28
The use of the Tablet PC encouraged me to pay attention to the material presented in the lectures or other in-person sessions.	5	1	19	21	20
The use of the Tablet PC helped me to understand the material presented in the lectures or other in-person sessions.	2	4	11	29	20

Table 2: Breakdown of responses for Survey 2

8. References

- Billman, A., Harding, A. & Engelbrecht, J. 2018. Does the chalkboard still hold its own against modern technology in teaching mathematics? A case study. *International Journal of Mathematical Education in Science and Technology*, 49, 809-823, <http://doi.org/10.1080/0020739X.2018.1431852>.
- Boyle, J. R., Forchelli, G. A. & Cariss, K. 2015. Note-taking interventions to assist students with disabilities in content area classes. *Preventing School Failure: Alternative Education for Children and Youth*, 59, 186-195, <http://doi.org/10.1080/10459881003785506>.
- Chandler, P. & Sweller, J. 1992. The Split-Attention Effect as a Factor in the Design of Instruction. *British Journal of Educational Psychology*, 62, 233-246, <http://doi.org/10.1111/j.2044-8279.1992.tb01017.x>.
- Day, R. S. The original teaching machine—The blackboard. *The Educational Forum*, 1967. Taylor & Francis, 195-201, <http://doi.org/10.1080/00131726709338041>.
- Ellis-Behnke, R., Gilliland, J., Schneider, G. & Singer, D. 2003. Educational benefits of a paperless classroom utilizing tablet PCs. *Massachusetts Institute of Technology, Cambridge, Massachusetts-USA*,
- Emerson, P. 1896. Ocean Circulation.—(II). *The Journal of Education*, 43, 330-331
- Fister, K. R. & McCarthy, M. L. 2008. Mathematics Instruction and the Tablet PC. *International Journal of Mathematical Education in Science and Technology*, 39, 285-292, <http://doi.org/10.1080/00207390701690303>.

- Galligan, L., Hobohm, C. & Loch, B. 2012. Tablet technology to facilitate improved interaction and communication with students studying mathematics at a distance. *Journal of Computers in Mathematics and Science Teaching*, 31, 363-385
- Gorgievski, N., Stroud, R., Truxaw, M. & Defranco, T. 2005. Tablet PC: A Preliminary Report on a Tool for Teaching Calculus. *International Journal for Technology in Mathematics Education*, 12, 95-102
- Greiffenhagen, C. 2014. The materiality of mathematics: Presenting mathematics at the blackboard. *The British journal of sociology*, 65, 502-528, <http://doi.org/10.1111/1468-4446.12037>.
- Hester, W. 1902. Promotion of Pupils. *The Journal of Education*, 56, 137-137
- Hoang, A., Tseng, W., Viswanathan, S. & Evans, H. 2009. Life Cycle Assessment of a Laptop Computer and its Contribution to Greenhouse Gas Emissions.
- Kohorst, K. & Cox, J. R. 2007. Virtual office hours using a tablet PC: E-Illuminating biochemistry in an online environment. *Biochemistry and Molecular Biology Education*, 35, 193-197, <http://doi.org/10.1002/bmb.50>.
- Lew, K., Fukawa-Connelly, T. P., Mejía-Ramos, J. P. & Weber, K. 2016. Lectures in advanced mathematics: Why students might not understand what the mathematics professor is trying to convey. *Journal for Research in Mathematics Education*, 47, 162-198, <http://doi.org/10.5951/jresmetheduc.47.2.0162>.
- Lin, C.-C., Lee, M.-K. & Huang, H.-L. 2015. Effects of chalk use on dust exposure and classroom air quality. *Aerosol and Air Quality Research*, 15, 2596-2608, <http://doi.org/10.4209/aaqr.2015.04.0216>.
- Maclaren, P., Wilson, D. & Klymchuk, S. 2017. I see what you are doing: Student views on lecturer use of Tablet PCs in the engineering mathematics classroom. *Australasian Journal of Educational Technology*, 33, <http://doi.org/10.14742/ajet.3257>.
- Majumdar, D. & William, S. P. 2009. Chalk dustfall during classroom teaching: particle size distribution and morphological characteristics. *Environmental monitoring and assessment*, 148, 343-351
- Mousavi, S. Y., Low, R. & Sweller, J. 1995. Reducing cognitive load by mixing auditory and visual presentation modes. *Journal of educational psychology*, 87, 319, <http://doi.org/10.1037/0022-0663.87.2.319>.
- Myyry, L., Kallunki, V., Katajavuori, N., Repo, S., Tuononen, T., Anttila, H., Kinnunen, P., Haarala-Muhonen, A. & Pyörälä, E. COVID-19 accelerating academic teachers' digital competence in distance teaching. *Frontiers in education*, 2022. Frontiers Media SA, 770094, <http://doi.org/10.3389/feduc.2022.770094>.
- Plasticseurope. 2022. *The Circular Economy for Plastics—A European Overview* [Online]. Available: <https://plasticseurope.org/knowledge-hub/the-circular-economy-for-plastics-a-european-overview-2/> [Accessed 20th March 2025].
- Rudow, S. R. & Finck, J. E. 2015. Pointing with Power or Creating with Chalk. *Contemporary Issues in Education Research*, 8, 123-134
- Sambrook, S. & Rowley, J. 2010. What's the use of webnotes? Student and staff perceptions. *Journal of Further and Higher Education*, 34, 119-134, <http://doi.org/10.1080/03098770903480338>.

- Schnackenberg, H. L. 2013. Tablet technologies and education. *International Journal of Education and Practice*, 1, 44-50
- Suleri, J. 2020. Learners' experience and expectations during and post COVID-19 in higher education. *Research in hospitality management*, 10, 91-96, <http://doi.org/10.1080/22243534.2020.1869463>.
- Ucas. 2023. *The shifting sands of student tech: What they're buying, how they're using it – and what this means for brands* [Online]. Available: <https://www.ucas.com/connect/blogs/shifting-sands-student-tech-what-theyre-buying-how-theyre-using-it-and-what-means-brands> [Accessed 7th March 2025].
- Wiggins, M. & Eglowstein, H. 2017. *A short history of the Hindsight Letterbug, circa 1986-1987* [Online]. Available: <http://www.overpricedsoftware.com/h87letterbug/> [Accessed 16th August 2024].
- Wylie, C. D. 2012. Teaching manuals and the blackboard: accessing historical classroom practices. *History of Education*, 41, 257-272, <http://doi.org/10.1080/0046760X.2011.584573>.

THIS PAGE
DELIBERATELY
LEFT BLANK

Revisiting John Snow's Cholera Map: A Data Visualisation Case Study for Statistical Education

Niamh Mimmagh, Department of Mathematics and Statistics, Maynooth University, Kildare, Ireland.
Email: <mailto:niamhmimmagh@gmail.com>

Abstract

Data visualisation is a fundamental tool in statistical analysis, enabling the identification of patterns and relationships that might otherwise remain hidden in raw data. One of the most famous historical examples is John Snow's 1854 cholera map, which demonstrated the spatial clustering of cholera cases around a contaminated water pump in London. This study explores how Snow's visualisation can be effectively incorporated into statistics education as an interactive case study. Revisiting Snow's cholera map in 2025 provides a powerful bridge between foundational epidemiological reasoning and modern statistical practice. It offers students an intuitive, historically grounded pathway into spatial thinking and data visualisation using tools like R. Using R, we outline the steps involved in reproducing Snow's cholera map, demonstrating geospatial data manipulation, visualisation techniques, and spatial analysis. We discuss the pedagogical benefits of historical case studies in statistics courses, emphasising their role in fostering curiosity, critical thinking, and technical proficiency. Additionally, we explore how these methods can be extended beyond epidemiology to applications in public health, urban analytics and environmental science. By integrating historical datasets with modern computational tools, educators can create engaging, hands-on learning experiences that reinforce core statistical principles while illustrating the real-world impact of data analysis.

Keywords: Visualisation, Exploratory Data Analysis, John Snow, Cholera, Spatial Data.

1. Introduction

Data visualisation plays an important role in statistical analysis and decision-making, allowing patterns and relationships to emerge that might otherwise remain hidden in raw data. One of the most famous early examples of discovery driven by visualisation comes from John Snow's 1854 cholera map (Snow, 1856), which is presented in Figure 1, and is widely recognised as a pioneering work in epidemiology and spatial statistics (Tufte and Robins, 1997). By plotting cholera cases on a street map of Soho, London, Snow succeeded in demonstrating a spatial pattern that linked cases to a contaminated water pump, providing critical evidence against the dominant miasma theory of disease transmission (Brody et al., 2000). His analysis contributed to the foundation of modern epidemiology and remains a compelling example of how statistical thinking, when combined with effective visualisation, can drive scientific progress (Friendly and Dennis, 2001).

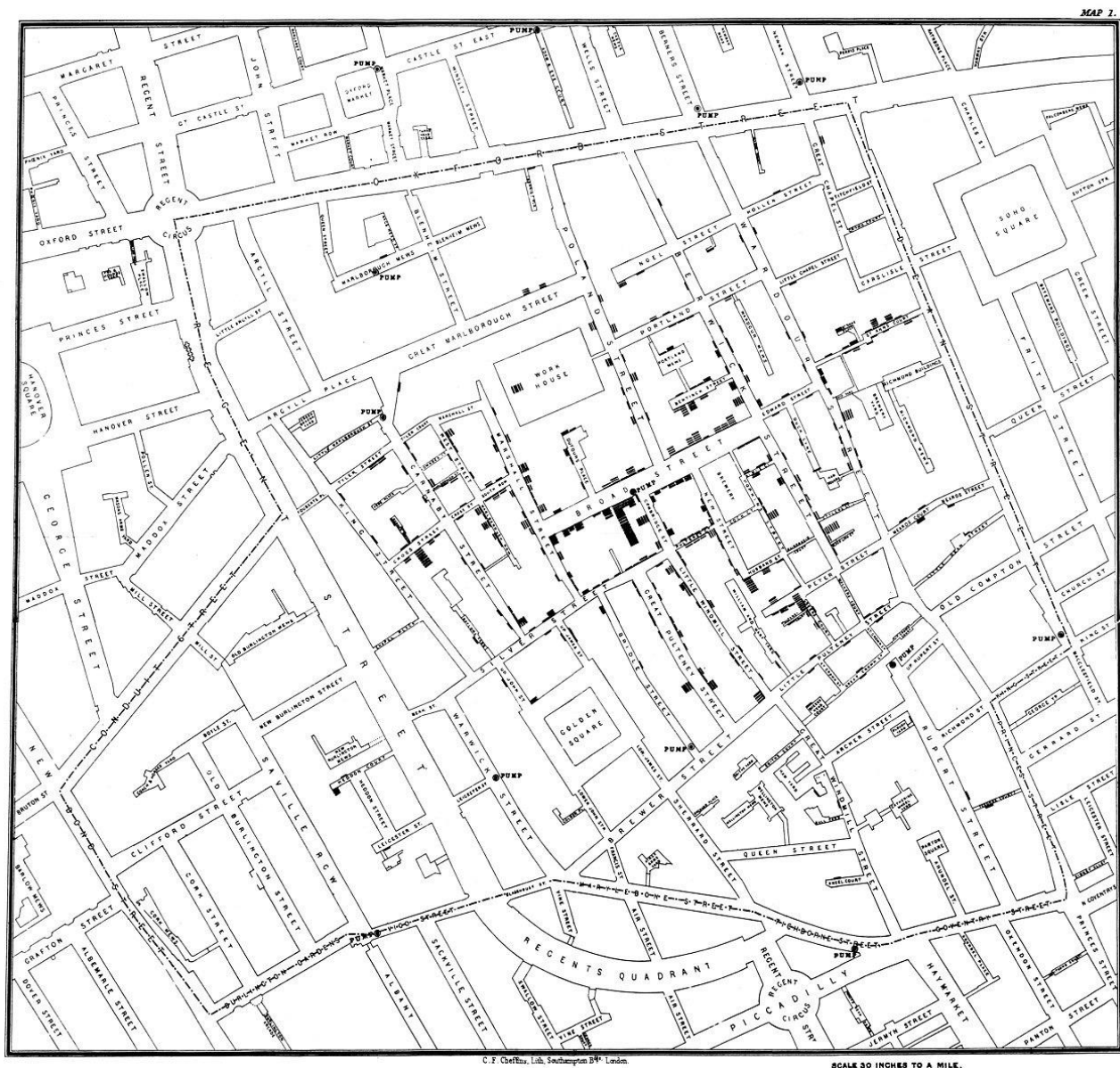


Figure 1: *John Snow's original 1854 cholera map of Soho, London.* This map visualises the spatial distribution of cholera deaths during the outbreak, revealing a clear clustering of cases around the Broad Street pump (centre-left of Broad Street). Water pumps are depicted as solid black circles, while cholera cases are shown as stacked black bars along the streets. The height of each bar corresponds to the number of deaths recorded at that location, enabling a street-level view of the outbreak's intensity.

Beyond its historical significance, John Snow's work serves as an excellent teaching tool for students learning about data visualisation, spatial analysis and statistical reasoning. The process of mapping the data, exploring patterns, and drawing inferences mirrors the methods used by statisticians and data scientists. In an era where computational tools such as R, Python and GIS (Geographic Information System) software enable increasingly sophisticated analyses, revisiting Snow's approach using contemporary methods offers a unique opportunity to engage students with both historical and modern perspectives on data science. Revisiting John Snow's cholera map in 2025 offers students a compelling, historically grounded introduction to spatial data analysis, especially in

an era where geospatial epidemiology and storytelling through data are integral to contemporary statistical practice and communication.

In this article, we explore how Snow's visualisation can be incorporated into statistics education as an interactive case study. Using R, we outline the steps involved in reproducing the cholera map, demonstrating how students can use geospatial data manipulation and visualisation techniques to uncover the same insights Snow did over 150 years ago.

Snow's case study provides a foundation for discussing widely used statistical techniques. For instance, bar plots and histograms can illustrate disease counts across different city districts, scatter plots can visualise spatial clustering, and kernel density estimation (KDE) can provide a smooth, continuous surface that highlights areas with higher concentrations of cases and can provide a modern alternative to Snow's hand-drawn map. Regression modelling can extend the case study to infer relationships between environmental factors and disease spread.

We also discuss the pedagogical benefits of using historical case studies in statistics courses, emphasising how they can foster curiosity, critical thinking, and technical proficiency. Finally, we consider how this approach can be extended beyond epidemiology, illustrating broader applications in public health, urban analytics, and environmental science, where similar data visualisation and modelling techniques are vital.

By blending historical datasets with modern computation techniques, we can create engaging, hands-on learning experiences that not only reinforce core statistical principles, but also help students appreciate the real-world impact of data analysis. Snow's cholera map is more than just a historical artifact, it is a powerful example of how data visualisation can reveal insights, shape scientific understanding, and drive evidence-based decision-making, making it an invaluable resource for a statistical education.

To fully realise the educational value of data visualisation, it is important to examine why visualisation plays such a central role in statistics education. Snow's map is more than historically significant. It embodies key principles of effective data storytelling, spatial reasoning, and analytical clarity. Before delving into the techniques involved in the recreation of the map, we first explore how visualisation fosters statistical thinking and why it remains a foundational skill in the modern data science classroom.

2. The Educational Value of Data Visualisation

Data visualisation is a fundamental tool in statistics education, allowing students to explore patterns, uncover relationships, and communicate insights effectively (Nolan and Perrett, 2016; Wilkerson et al., 2025). As Baumer et al. (2022) describe, it is "one of the most accessible, compelling, and expressive modes to investigate and depict patterns in data." Unlike raw numerical summaries, visual representations provide an intuitive and immediate understanding of complex datasets. When raw data is translated into visual form, it becomes easier to interpret, allowing observers to quickly identify trends, anomalies, and key insights (Kirk, 2021). Whether through scatter plots, histograms or geospatial maps, visualisation helps students bridge the gap between abstract statistical concepts and real-world interpretation (Chang et al., 2024).

John Snow's 1854 cholera map offers a compelling case study in this regard. By plotting cholera cases spatially, Snow was able to reveal an epidemiological pattern that was not immediately obvious from tabular data alone. This example underscores a key lesson for students: data visualisation is not just about making data look appealing - it is a vital step in the analytical process

that can lead to new discoveries and enables more informed decision-making (Tukey et al., 1977; Unwin, 2020; Newburger & Elmqvist, 2023; Bach et al., 2023).

In modern statistics and data science curricula, incorporating historical case studies like Snow's cholera map can serve multiple educational purposes:

1. Enhancing Statistical Thinking

By visualising the spread of cholera cases, students engage in exploratory data analysis, a crucial step in any statistical workflow. This encourages pattern recognition, hypothesis generation and critical thinking, skills that are essential for informed decision-making. It also reinforces the idea that data should be represented visually before any formal modelling begins (Tukey, 1972; Baumer et al., 2022), as unexpected insights may emerge.

2. Introducing Spatial Data and Geographic Information Systems

Traditional statistics courses often focus on numerical and categorical data, but spatial data introduces new dimensions of analysis. Snow's map allows students to work with coordinate-based data, spatial clustering techniques, and geospatial visualisation tools in R (Unwin, 2018). It also serves as an introduction to Geographic Information Systems (GIS) - computer-based tools for capturing, analysing, and visualising spatial data - which are widely used in fields such as epidemiology, urban planning, and environmental science (Cromley and McLafferty, 2011).

3. Connecting Historical Data to Modern Applications

Many of the same principles Snow applied in the 19th Century are used today in public health monitoring, pandemic modelling and risk assessment. Students can draw parallels between Snow's cholera outbreak investigation and modern epidemiological studies, such as COVID-19 hotspot mapping (Franch-Pardo et al., 2020; Zhang and Schwartz, 2020) or air pollution analysis (Brunekreef and Holgate, 2002), which can use interactive features to enhance storytelling (Li, 2024). This connection reinforces the relevance of statistical reasoning beyond the classroom.

4. Encouraging Computational Skill Development

Implementing Snow's visualisation in R introduces students to essential programming concepts, including data wrangling (e.g. dplyr (Wickham, François, et al. 2023) and tidyverse (Wickham, Averick, et al., 2019)), geospatial mapping (e.g. ggplot2 (Wickham, 2016) and sf (Pebesma and Bivand, 2023; Pebesma, 2018)), and reproducible research practices. This hands-on experience helps student build confidence in working with real-world data and computational tools. It demonstrates how open-source software can be used for both historical data analysis and contemporary statistical applications

By integrating historical data visualisation projects into statistics education, instructors can create engaging, interdisciplinary learning experiences that blend historical inquiry, data science and statistical reasoning. John Snow's cholera map is not just an artifact of epidemiological history; it is a timeless example of the power of data visualisation as an investigative and educational tool.

With this pedagogical foundation in place, we turn now to the practical implementation of this case study. Using R, students can bring this historical dataset to life, gaining firsthand experience with geospatial data, visualisation techniques, and computational workflows. The following section outlines how to recreate Snow's cholera map step by step, highlighting the technical process and the educational opportunities it offers.

3. Recreating John Snow's Map Using R

Reconstructing John Snow's 1854 cholera map using modern statistical tools provides an engaging hands-on exercise for students learning data visualisation, geospatial analysis and epidemiological

modelling. With R, we can replicate Snow's approach by using real historical data, reinforcing key statistical concepts while demonstrating the way computation tools enhance our ability to analyse and visualise spatial data.

In this section, we outline the key steps involved in reproducing Snow's map using R, focusing on data acquisition, spatial visualisation and interpretation.

3.1 Preparing the Data

To recreate the cholera map, we first need data on:

- Cholera cases: the locations where cholera deaths were recorded.
- Water pumps: The suspected sources of contamination.
- Street layout: the geographical context for visualisation.

These datasets are available from historical sources and have been digitised for analysis in R. The `SnowData` package (Mimnagh, 2025) provides a clean version of Snow's data, which can be loaded as follows:

```
# Load required packages and data
library(ggplot2)
library(sf)
library(dplyr)
library(SnowData)
data(cholera_cases)
data(pump_locations)
```

At this stage, we have two key spatial datasets: one containing the cholera deaths and another with the water pump locations.

3.2 Mapping Cholera Cases and Water Pumps

Next, we visualise the data using `ggplot2`, overlaying the cholera cases and water pumps onto a simple map.

```
# Plot cholera deaths (red) and water pumps (blue)

ggplot() +
  geom_point(data = cholera_cases, aes(x = Easting, y = Northing),
            color = "red", alpha = 0.6, size = 2) + # Plot deaths as semi-
transparent red circles
  geom_point(data = pump_locations, aes(x = Easting, y = Northing),
            color = "blue", size = 4, shape = 17) + # Plot pumps as blue triangles
  labs(title = "John Snow's 1854 Cholera Map",
       subtitle = "Red circles = Cholera deaths, Blue triangles = Water pumps") +
  theme_minimal() # Use a clean background
```

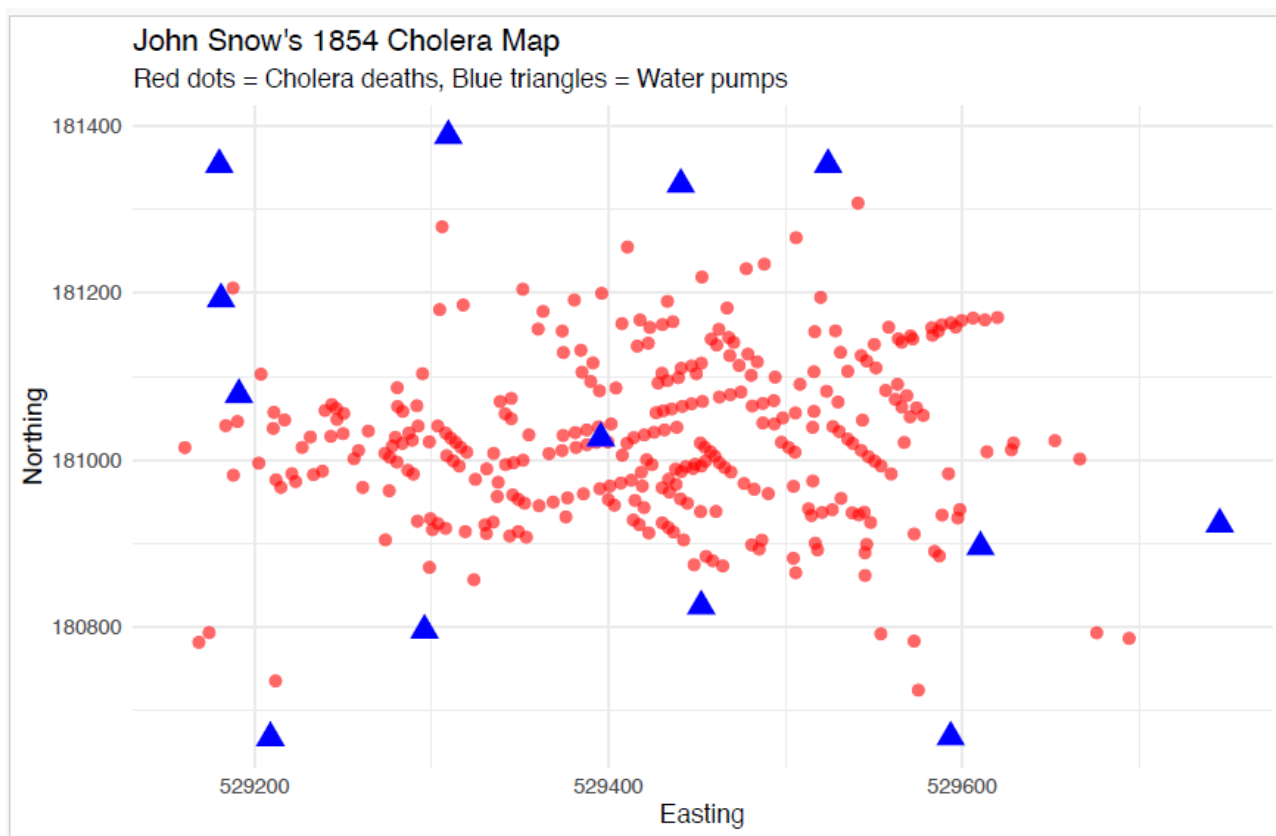


Figure 2: *Cholera cases and water pump locations during the 1854 Broad Street outbreak.* Cholera deaths are plotted as red circles and water pumps as blue triangles using coordinates from the British National Grid (EPSG:27700), with Easting and Northing on the x- and y-axes, respectively. Although no street map is shown, the spatial clustering of cases around the central Broad Street pump is clearly visible, illustrating the geographic concentration of the outbreak.

This initial visualisation highlights the spatial clustering of cholera cases around certain water pumps, reflecting Snow's original analysis.

3.3 Adding Street Layout for Context

To make the visualisation more informative, we can overlay the data onto the original street map. This can be achieved using a digitised version of Snow's map, available as part of the SnowData package, or OpenStreetMap data.

```
library(osmdata)
# SnowData uses the British National Grid (EPSG:27700), so we define the bounding
box using the same projection
soho_bbox_27700 <- st_bbox(c(xmin = 529150.0, ymin = 180720.6,
                           xmax = 529750.9, ymax = 181370.5),
                        crs = st_crs(27700))

# Transform bounding box to WGS84 (EPSG:4326) for OpenStreetMap API request
soho_bbox_4326 <- st_bbox(st_transform(st_as_sfc(soho_bbox_27700), crs = 4326))

# Request street data for roads ("highway") from OpenStreetMap
streets <- opq(bbox = soho_bbox_4326) %>%
```

```

add_osm_feature(key = "highway") %>%
osmdata_sf()

# Convert retrieved street data to EPSG:27700 to match Snow dataset
streets <- st_transform(streets$osm_lines, crs = 27700)

# Plot street network, cholera deaths, and pumps in projected space
ggplot() +
  geom_sf(data = streets, color = "gray50", size = 0.5)+ # OSM streets
  geom_point(data = cholera_cases,
             aes(x = Easting, y = Northing),
             color = "red", alpha = 0.6) + # Overlay deaths
  geom_point(data = pump_locations,
             aes(x = Easting, y = Northing),
             color = "blue", shape = 17) + # Overlay pumps
  theme(panel.grid = element_blank(), # Clean up background
        axis.title.x = element_blank(),
        axis.title.y = element_blank(),
        panel.background = element_rect(fill = "white"),
        plot.background = element_rect(fill = "white")) +
  coord_sf(crs = 27700, datum = st_crs(27700)) # Ensure correct spatial reference

```

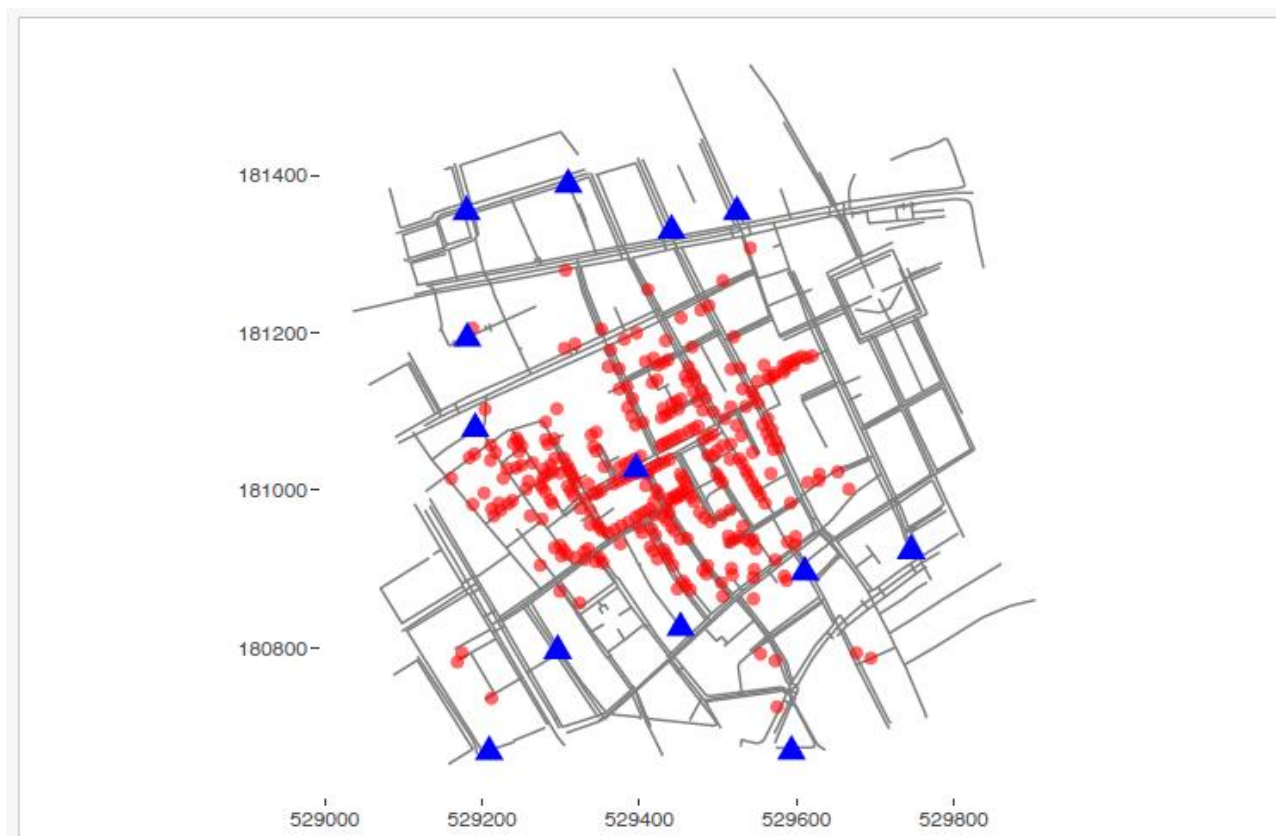


Figure 3: *Cholera cases and water pump locations overlaid on the 1854 Soho street-network.* Red circles represent individual cholera deaths, while blue triangles mark the positions of water pumps. The underlying street map provides geographic context, highlighting how cholera cases cluster near the Broad Street pump. This spatial pattern supports John Snow's hypothesis of a waterborne source of the outbreak.

Alternatively, as a more complicated exercise, students may attempt to accurately recreate John Snow's original 1854 map. Students may begin by loading the georeferenced map to use as a background.

```
map <- load_map() # Load base raster map for background
data(cholera_cases)
data(pump_locations)
library(rasterVis)
library(tidyr)
```

John Snow's original map represents the cholera outbreak in the Soho district of London, showing the locations of cholera deaths as black bars stacked along the streets. To create this plot, students must generate these bars and rotate them accordingly. This can be done using a user-defined function, and Angle and Count columns in the cholera cases dataset, to specify the necessary angle of rotation and the height of the black bars, respectively.

```
# Custom function to build bar-style rectangles, rotated to match the street
orientation
rotate_rectangle <- function(x, y, count, angle) {
# Trigonometry functions in R expect radians so we convert from degrees.
  theta <- angle * pi / 180
# Width is fixed, and height is controlled by death count
  hw <- 2      # Fixed width for each bar
  hh <- count  # Bar height scaled by death count

# Define the four corners of a rectangle centred at the origin (0,0)
# The rectangle has a fixed width (hw) and a height (hh) proportional to the
number of cholera deaths
corners<-matrix(c(-hw, 0,      # Bottom-left: x = -hw (left of centre), y=0
                  hw, 0,      # Bottom-right: x = +hw (right of centre), y=0
                  hw, hh,     # Top-right: x = +hw, y = hh (height above base)
                  -hw, hh),   # Top-left: x = -hw, y = hh (same as top-right)
                ncol = 2, byrow = TRUE)

# Define a 2D rotation matrix to rotate the rectangle by a given angle (theta)
# This matrix will rotate points counterclockwise around the origin
rotation_matrix <- matrix(c(cos(theta), -sin(theta),
                             sin(theta),  cos(theta)), ncol = 2)

# Rotate the rectangle corners using matrix multiplication
rotated_corners <- corners %*% rotation_matrix

# Convert rotated corner coordinates into a data frame for plotting
rotated_corners <- data.frame(rotated_corners)
colnames(rotated_corners) <- c("x", "y")

# The rotated rectangle is currently centred at (0,0), we want to shift it to its
correct map position (x,y)
rotated_corners$x <- rotated_corners$x + x
rotated_corners$y <- rotated_corners$y + y

return(rotated_corners)
}
# Generate a rotated rectangle for each cholera case
# Height is scaled by Count*2 to match the proportional bar heights in Snow's
original map
rectangles <- cholera_cases %>%
  rowwise() %>%
  mutate(corners = list(rotate_rectangle(Easting, Northing, Count * 2, Angle)))
%>%
```



```

# Expand the list of corners into individual rows for plotting polygons
unnest(corners) %>%
ungroup() %>%

# Assign a unique group ID to each rectangle (used to draw polygons correctly)
mutate(id = rep(1:nrow(cholera_cases), each = 4))

# Plot map with rotated bars (as in Snow's original)
ggplot(map, maxpixels = 5e6) + # Background raster
  geom_tile(aes(fill = value)) +
  scale_fill_gradient(low = 'black', high = 'white') +
  geom_point(data = pump_locations,
            aes(x = Easting, y = Northing),
            colour = "blue") +
  geom_polygon(data = rectangles,
            aes(x = x, y = y, group = id),
            color = "black") +
  theme(axis.text.x = element_blank(),
        axis.title.x = element_blank(),
        axis.text.y = element_blank(),
        axis.title.y = element_blank(),
        axis.line = element_blank(),
        legend.position="none")

```



Figure 4: *Reproduction made with R of John Snow's 1854 cholera map, showing cholera cases and water pumps overlaid on the original street layout of Soho. Cholera deaths are represented as stacked black bars along the streets, with bar height indicating the number of deaths at each location. Water pumps are shown as blue circles. This historically faithful visualisation mirrors Snow's original approach and illustrates how spatial clustering of cases near the Broad Street pump provided evidence for his theory of waterborne transmission.*

The resulting map is slightly warped due to stretching that occurred during the georeferencing process, in which the original 1854 map was aligned to modern geographic coordinate systems. This distortion arises because historical maps can lack consistent scale, orientation, or reference points, making precise alignment with modern spatial data challenging. Such warping is common when working with historical spatial sources, particularly those that were hand-drawn or created before the standardisation of cartographic projection systems. Despite this, georeferencing enables students to overlay historical and modern spatial data, offering a compelling and context-rich view of Snow's findings while introducing practical challenges frequently encountered in spatial data analysis.

3.4 Interpreting the Results

Once the map is complete, students can explore spatial clustering and discuss key takeaways:

- The high concentration of cholera deaths around a single water pump (Broad Street pump) supports Snow's hypothesis.
- Some deaths occur further away, leading to discussions of outliers, confounding factors and alternative explanations - in interviewing Soho residents, John Snow found that some of those who died from cholera were known to prefer to collect water from the Broad Street pump even though it was not their nearest pump (Brody et al., 2000).
- Additional analytical techniques, such as spatial point pattern analysis, can be introduced to further explore the data.

For example, students could calculate the distance from each cholera case to the nearest water pump to quantify spatial patterns.

```
data(streets)
# Ensure all coordinate columns are numeric
streets <- streets %>% mutate(across(everything(), as.numeric))

# Convert start and end points into LINESTRING geometries
streets <- streets %>%
  rowwise() %>%
  mutate(geometry = st_sfc(st_linestring(matrix(c(start_coord_east,
                                                    start_coord_north, end_coord_east,
                                                    end_coord_north), ncol = 2,
                                                    byrow = TRUE)))) %>%

  ungroup() %>%
  st_as_sf(crs = 27700) # Convert to spatial object with British Grid CRS

# Convert point data for cases and pumps into spatial (sf) format
cholera_cases <- st_as_sf(cholera_cases,
                          coords = c("Easting", "Northing"),
                          crs = 27700)
pump_locations <- st_as_sf(pump_locations,
                          coords = c("Easting", "Northing"),
                          crs = 27700)

# Identify nearest pump to each cholera case
cholera_cases <- cholera_cases %>%
  mutate(nearest_pump = st_nearest_feature(geometry,
                                            pump_locations$geometry,
                                            dist = as.numeric(min(st_distance(geometry,
                                            st_geometry(pump_locations))))))
```

```
# Create a connecting LINESTRING between each death and its nearest pump
connections <- cholera_cases %>%
  rowwise() %>%
  mutate(line = st_sfc(st_cast(st_union(geometry,
    pump_locations$geometry[nearest_pump]), "LINESTRING")) %>%
    ungroup() %>% st_as_sf())

# Assign color based on pump ID
connections$pump_id<-as.factor(connections$nearest_pump)

# Plot deaths, pumps, and connecting lines
ggplot() +
  geom_sf(data = connections, aes(geometry = line, color = pump_id)) + #
Connections
  geom_sf(data = cholera_cases, color="black", size = 0.5, alpha = 0.8) + #
Deaths
  geom_sf(data = pump_locations, color = "red", size = 3, pch = 8) + # Pumps
  geom_sf(data = streets, alpha = 0.2)+ # Street background
  theme_minimal() +
  labs(color = "Pump ID")
```

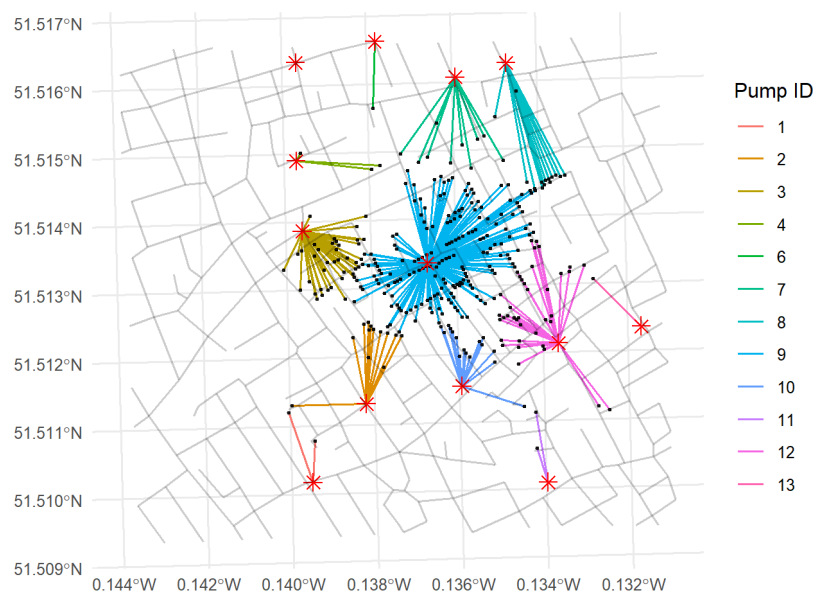


Figure 5: *Cholera cases, water pumps, and spatial connections during the 1854 Soho outbreak.* Black circles represent individual cholera deaths, and red stars indicate water pump locations. Each case is connected by a line to its nearest pump using Euclidean distance, with line colours distinguishing different pumps. Overlaid on the Soho street network, this modern spatial visualisation highlights potential zones of influence and reinforces John Snow's hypothesis that the outbreak was linked to a contaminated water source - particularly the Broad Street pump.

Figure 5 overlays cholera deaths and water pump locations onto the street network and connects each death to its nearest pump using straight lines (Euclidean distance). These connecting lines are colour-coded by pump ID, visually grouping deaths by their closest water source. This highlights clusters of cases associated with specific pumps - notably the dense cluster around the Broad Street pump. By examining which pumps are associated with more deaths, students can explore the spatial

distribution of risk. This type of representation also allows discussions about spatial assumptions: although lines show the shortest possible distance "as the crow flies," they do not account for actual street layouts.

The visualisations presented in Figures 4 and 5 offer complementary perspectives on the 1854 cholera outbreak. Figure 4 prioritises historical fidelity by replicating the original visual language of Snow's map - specifically, the stacked bars representing cholera deaths along streets - preserving the intuitive representation of deaths that Snow himself used to draw causal inferences. This allows students to appreciate the historical context and reasoning behind the original analysis. In contrast, Figure 5 introduces a more modern spatial visualisation by connecting each cholera case to its nearest water pump using Euclidean distance lines. While this approach offers analytical clarity and facilitates computational spatial analysis, it also abstracts away from the lived urban geography - ignoring street layouts and accessibility. Discussing both versions with students can deepen their understanding of how visual representation shapes analytical interpretation. It also highlights an important pedagogical point: modern tools can enhance precision and enable new kinds of analysis, but they may also impose assumptions that diverge from historical or practical realities.

3.5 Extending the Analysis

Once students have recreated Snow's map, they can modify the visualisation and extend their analysis in several ways:

- Comparing different visualisation types (e.g. point maps versus density plots as in Parker and Bahrami (2021)).
- Adding interactivity using shiny or leaflet to explore data dynamically.
- Applying similar methods to modern epidemiological datasets (e.g., COVID-19 case data).
- Performing predictive modelling using machine learning to identify potential hotspots based on simulated data.

These extensions help reinforce the practical applications of spatial statistics in real-world scenarios.

Recreating John Snow's cholera map using R is an effective way to teach students the power of data visualisation in statistics. This exercise introduces key concepts in exploratory data analysis, geospatial statistics and epidemiology, while also building practical computational skills.

4. Pedagogical Considerations and Applications

The recreation of John Snow's cholera map using R offers a rich opportunity for educators to introduce students to key concepts in data visualisation, spatial statistics and epidemiology. However, to maximise the educational impact of this exercise, instructors should consider how best to structure the activity, tailor it to different levels of student experience, and connect it to broader statistical and data science principles.

In this section, I outline practical strategies for incorporating this case study into statistics education, discuss common challenges and solutions, and suggest extensions that can help students deepen their understanding of spatial analysis and epidemiological modelling.

4.1 Integrating the Activity into a Statistics Curriculum

The John Snow cholera case study can be integrated into a variety of statistics and data science courses, including:

- Introductory Statistics: Teaching basic data visualisation, exploratory data analysis, and the importance of graphical methods in discovering patterns.
- Applied Data Science: Demonstrating the power of geospatial analysis and reproducible research using R.
- Public Health and Epidemiology: Connecting statistical reasoning to real-world disease modelling and outbreak investigation.
- History of Statistics: Providing a historical perspective on data-driven decision-making and how early statisticians shaped modern scientific inquiry.

Following the guidance of Cobb (1992), instructors may choose to structure the activity as:

- A guided tutorial, where students follow a step-by-step replication of John Snow's analysis.
- An open-ended project, where students experiment with different visualisation techniques and alternative datasets.
- A discussion-based case study, using Snow's map as a starting point for critical thinking about data ethics, causality and statistical inference.

To make implementation more concrete, Table 1 outlines suggested learning outcomes, classroom activities, and assessment strategies aligned with this case study. These are adaptable to different levels of statistical expertise, from introductory courses to applied data science modules.

Table 4: Suggested Learning Outcomes, Activities, and Assessments for Integrating the John Snow Case Study.

Learning Outcome	Classroom Activity	Assessment Strategy
Interpret and visualise spatial data using R	Recreate Snow's map using cholera and pump datasets with ggplot and sf	Submit a reproducible report explaining each visualisation step
Explain the role of visualisation in hypothesis generation	Class discussion comparing Figures 4 and 5; prompt: "How can visualisation shape interpretation?"	Reflective essay: "What can we learn from a map?"
Use spatial reasoning to identify clustering and spatial patterns	Calculate nearest-pump connections and discuss outliers and exceptions	Short quiz on spatial measures (e.g., Euclidean vs. real-world distance)
Connect historical analysis to modern public health data	Compare Snow's outbreak data to COVID-19 hotspot or air pollution maps	Group project: Apply same pipeline to a modern dataset and present findings
Evaluate ethical and practical implications of epidemiological data visualisation	Debate: "Do data visualisations clarify or obscure public understanding of risk?"	Group project: Identify and discuss potential biases, privacy issues and misinterpretations in visualisations

4.2 Common Challenges and How to Address Them

While the John Snow case study is engaging and historically significant, students may encounter several challenges when working with geospatial data in R, including those detailed by Kross and Guo (2019). Below in Table 2 are some potential difficulties and strategies for addressing them.

Table 2: Challenges that may arise in implementing the John Snow case study, and potential solutions

Challenge	Solution
Students unfamiliar with R	Provide starter code and structured walk-throughs to build confidence
Geospatial data concepts are new	Begin with simple visualisations (scatter plots) before introducing spatial mapping tools
Data manipulation is complex	Use tidyverse functions to introduce step-by-step data transformation
Students struggle with interpreting spatial patterns	Use interactive tools (RShiny, leaflet) to allow dynamic exploration of the data
Linking historical insights to modern applications	Assign follow-up tasks using current datasets (e.g., COVID-19 cases, air pollution data)

By anticipating these difficulties, educators can structure the learning process effectively and ensure that students engage with the material in a meaningful way.

4.3 Extending the Case Study for Deeper Learning

Once students have successfully recreated Snow's map, instructors can encourage further exploration through additional activities:

1. Data Interpretation and Statistical Inference
 - Ask students to quantify the clustering of cholera cases using nearest-neighbour distances or spatial autocorrelation methods.
 - Compare different visualisation methods, such as heatmaps, density plots or contour plots, to illustrate how different graphical techniques highlight patterns
2. Apply Spatial Analysis to Modern Data
 - Extend the methods learned in this case study to modern epidemiological data (e.g. COVID-19 cases, influenza outbreaks).
 - Use open datasets (e.g. public health, crime data) to explore spatial clustering in different contexts.
 - Compare Snow's approach to modern machine learning methods for disease mapping and risk prediction.
3. Creating an Interactive Shiny App
 - Students with programming experience can build an interactive Shiny dashboard that allows users to explore data dynamically.
 - By incorporating slider controls, hover-over tooltips, and filtering options, students can experiment with making data visualisations more engaging and accessible.

4. Ethical Discussions on Data-Driven Decision-Making

- Snow's work ultimately influenced public health policy by leading to improvements in sanitation infrastructure.
- Ask students to discuss modern ethical considerations in epidemiological modelling, such as data privacy, bias in disease surveillance, and the use of AI for outbreak prediction.

4.4 Reflections on the Educational Value of Historical Case Studies

Using historical examples like John Snow's cholera map provides students with more than just technical skills, it also helps them develop an appreciation for the role of statisticians in shaping scientific knowledge. This case study reinforces several broader lessons.

- The importance of visualisation in statistical discovery: Snow's work illustrates that seeing patterns in data is often the first step in generating hypotheses.
- The power of interdisciplinary thinking: Combining spatial data, medical knowledge and statistical reasoning led to statistical advancement.
- The value of open data and reproducibility: By recreating Snow's map in R, students engage in the same investigative process that epidemiologists and data scientists use today.

Through hands-on exploration, students not only gain computational and analytical skills, but also develop a deeper understanding of how statistics contributes to real-world problem-solving. This blend of technical knowledge, historical context, and critical thinking makes the John Snow cholera map an exceptional teaching tool for modern statistics education.

These pedagogical insights underscore the enduring relevance of Snow's work in today's data-driven world. As educators look to the future, the integration of historical case studies with modern analytical tools offers a promising model for teaching statistics in a way that is both rigorous and engaging. In the concluding section, we reflect on the broader implications of this approach and suggest potential directions for further development and adaptation.

5. Conclusions

John Snow's cholera map remains a compelling example of how visualisation and statistical reasoning can uncover hidden patterns and drive change. By recreating and analysing this historical case study, students engage with foundational concepts in spatial statistics and epidemiology while developing computational skills essential for modern data science.

Through this exercise, learners gain experience in data wrangling and geospatial visualisation using R packages, exploratory data analysis and pattern recognition in a real-world dataset, and critical thinking about statistical inference and causality, using a case where evidence led to major public health interventions.

Additionally, this pedagogical approach highlights the interdisciplinary nature of statistical thinking, connecting historical data analysis with contemporary public health and policy applications. The ability to bridge historical insights with modern computational methods fosters a deeper appreciation for the evolving role of statistics in decision-making.

While John Snow's cholera map is an ideal case study for teaching spatial statistics, the underlying principles can be extended to many other datasets. Future implementations of this approach could include:

- Contemporary Public Health

Analysing COVID-19 case distributions, vaccination uptake or air pollution data, and comparing different data visualisation techniques to communicate health risks effectively.

- Environmental and Climate Data

Exploring spatial patterns in climate-related data, such as temperature anomalies or flood occurrences.

- Urban Analytics and Social Science Applications

Using geospatial data to analyse crime rates, or transportation networks and examining spatial clustering in these datasets.

By incorporating these extensions, educators can adapt this historical case study into a versatile framework for teaching modern data science skills.

The use of historical case studies in teaching statistics provides an engaging, tangible way to illustrate core concepts while also highlighting the societal impact of data-driven decision-making. By revisiting Snow's work through a modern computation lens, not do we only honour one of the earliest applications of spatial statistics but also equip students with the skills to tackle today's pressing data analysis challenges.

6. References

- Bach, B., Keck, M., Rajabiyazdi, F., Losev, T., Meirelles, I., Dykes, J., ... & Carpendale, S. (2023). Challenges and opportunities in data visualization education: A call to action. *IEEE Transactions on visualization and computer graphics*, 30(1), 649-660.
- Baumer, B. S., Kaplan, D. T., & Horton, N. J. (2017). *Modern data science with R*. Chapman and Hall/CRC.
- Brody, H., Rip, M. R., Vinten-Johansen, P., Paneth, N., & Rachman, S., 2000. Map-making and myth-making in Broad Street: The London cholera epidemic, 1854. *The Lancet*, 356 (9223), 64–68.
- Brunekreef, B., & Holgate, S. T., 2002. Air pollution and health. *The Lancet*, 360 (9341), 1233–1242.
- Chang, H. Y., Chang, Y. J., & Tsai, M. J. (2024). Strategies and difficulties during students' construction of data visualizations. *International Journal of STEM Education*, 11(1), 11.
- Cobb, G., 1992. Teaching statistics. *Heeding the call for change: Suggestions for curricular action*, 22, 3–43.
- Cromley, E. K., & McLafferty, S. L., 2011. GIS and public health. *Guilford Press*.
- Franch-Pardo, I., Napoletano, B. M., Rosete-Verges, F., & Billa, L., 2020. Spatial analysis and GIS in the study of covid-19. a review. *Science of the total environment*, 739, 140033.

Friendly, M., & Denis, D. J., 2001. *Milestones in the history of thematic cartography, statistical graphics, and data visualization*. [online] Available at: <http://www.datavis.ca/milestones> [Accessed 07 March 2025]

Kross, S., & Guo, P. J., 2019. Practitioners teaching data science in industry and academia: Expectations, workflows, and challenges. *Proceedings of the 2019 CHI conference on human factors in computing systems*, 1–14.

Li, M. (2024). Incorporating Data Visualisation into Teaching and Learning. *Mathematics Education Research Group of Australasia*.

Mimnagh, N., 2025. *SnowData: Historical data from John Snow's 1854 cholera outbreak map* [R package version 1.0.0]. Available at: <https://CRAN.R-project.org/package=SnowData>

Newburger, E., & Elmqvist, N. (2023). Visualization according to statisticians: an interview study on the role of visualization for inferential statistics. *IEEE transactions on visualization and computer graphics*, 30(1), 230-239.

Nolan, D., & Perrett, J., 2016. Teaching and learning data visualization: Ideas and assignments. *The American Statistician*, 70 (3), 260–269.

Parker, R., & Bahrami, M. (2021, August 3). *John Snow: The birth of epidemiology, data analysis & visualization*. Wolfram Blog. <https://blog.wolfram.com/2021/08/03/john-snow-the-birth-of-epidemiology-data-analysis-visualization/>

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, 10 (1), 439–446. <https://doi.org/10.32614/RJ-2018-009>

Pebesma, E., and Bivand, R., 2023. *Spatial Data Science: With applications in R*. Chapman and Hall/CRC.

Snow, J., 1856. On the mode of communication of cholera. *Edinburgh medical journal*, 1 (7), 668.

Tufte, E. R., and Robins, D., 1997. *Visual explanations*. Graphics Cheshire, CT.

Tukey, J. W., 1972. Some graphic and semigraphic displays. *Statistical papers in honor of George W. Snedecor*, 5, 293–316.

Tukey, J. W., et al., 1977. *Exploratory data analysis* (Vol. 2). Springer.

Unwin, A., 2018. *Graphical data analysis with R*. Chapman; Hall/CRC.

Unwin, A., 2020. Why is data visualization important? what is important in data visualization. *Harvard Data Science Review*, 2 (1), 1.

Wickham, H., 2016. *Ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Golemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. *Journal of Open Source Software*, 4 (43), 1686. <https://doi.org/10.21105/joss.01686>

Wickham, H., François, R., Henry, L., Müller, K., & Vaughan, D., 2023. *Dplyr: A grammar of data manipulation* [R package version 1.1.4] Available at: <https://dplyr.tidyverse.org>

Wilkerson, M. H., Kim, J., Lee, H. S., Stokes, D. J., & Ferrell, M. (2025). How Teachers Envision Using Data Visualization Discussion Tasks in Classroom Instruction. *International Journal of Science and Mathematics Education*, 1-35.

Zhang, C. H., & Schwartz, G. G., 2020. Spatial disparities in coronavirus incidence and mortality in the United States: An ecological analysis as of May 2020. *The Journal of Rural Health*, 36 (3), 433–445.

OPINION

Breaking free: motivating mathematics through escape rooms

Thomas E. Woolley, School of Mathematics, Cardiff University, UK. Email: woolleyt1@cardiff.ac.uk

Abstract

Escape rooms provide a unique and engaging way to promote mathematical thinking by embedding problems within a narrative-driven environment. This opinion piece highlights the effectiveness of escape rooms as a pedagogical tool, their ability to foster problem-solving skills, teamwork, and motivation among students. The study details the design principles used to create mathematical escape rooms, incorporating puzzles that require keen observation, logical reasoning and pattern recognition. Practical considerations, such as difficulty scaling and accessibility, are discussed, ensuring these activities cater to a diverse audience. By presenting mathematics in an immersive and interactive format, escape rooms encourage exploration and perseverance, ultimately improving students' confidence in tackling mathematical challenges.

Keywords: Escape rooms, Mathematical thinking, Problem-solving, Engagement.

1. Introduction

Being a mathematician, I have always enjoyed puzzles. I love unravelling a mystery and seeing a solution form before my eyes. Moreover, I enjoy playing board games with friends. While it is great to win, it is perhaps more interesting to observe the interactions between players and watch their strategies unfold. Through these two hobbies, I developed an interest in escape rooms.

For those unfamiliar, an escape room is an interactive game where a group of participants work together to solve puzzles, discover clues, and complete challenges to achieve a goal (such as escaping a room) within a set time limit. Critically, escape rooms are often themed, and no matter whether the scenario involves defusing a bomb, exploring ancient temples, or cracking alien codes, the joy of solving puzzles with friends against the clock is unparalleled.

This enthusiasm, coupled with my role as Head of Outreach in the School of Mathematics, inspired me to create a mathematical escape room. My goal was simple: to excite and motivate students about mathematics in a way that is both engaging and memorable. The goal of this article is equally straightforward: I want to convince you that creating a mathematical escape room is a beneficial addition to any outreach programme. It engages children and adults alike and leaves participants with a positive memory of mathematics.

Creating an escape room requires effort and money. By following my thoughts below and using all of my materials, hosted online for free at bit.ly/EscapeRoomMaterial, these challenges should be significantly reduced. Furthermore, an equipment list and solution structure are included in Appendices A and B, respectively.

2. Educational benefits

Of course, I am not the first person to use escape rooms for educational purposes. Their ability to combine narrative-driven challenges with teamwork and critical thinking has made them increasingly popular in classrooms. Studies have shown that these activities foster key skills such as collaboration, problem-solving, and resilience (Taraldsen, et al., 2022; Veldkamp, et al., 2020).

However, careful design is essential; aligning game mechanics with educational objectives is critical to achieving meaningful learning outcomes, rather than producing a set of trivialities.

When done well, the immersive nature of escape rooms keeps students focused. Unlike traditional classroom settings, where some students may feel disengaged, escape rooms encourage active participation. For example, in a classroom, if a technique is taught, students will grasp the concept at different speeds. Those who understand the work tend to push ahead, leaving others feeling that they can offer little to discussions that have not already been covered.

In an escape room, as long as it is focused on problem-solving and not dependent on prior knowledge, all participants are on the same footing. They do not know what tasks they are going to have to do, nor do they know what skills they will need. Moreover, their different lived experiences allow them to view problems in unique ways, which is crucial for team problem-solving. Thus, as clues appear, everyone is encouraged to contribute their thoughts because no one knows which answer will pan out best. This reduces learning anxiety and increases motivation (Fotaris & Mastoras, 2019).

However, implementing escape rooms in educational contexts presents challenges. Designing puzzles that strike the right balance between accessibility and complexity is a nuanced process. Additionally, ensuring that all participants can contribute, regardless of their prior knowledge, requires careful planning.

3. Design considerations

When developing the mathematical escape room, I carefully considered several factors to ensure its effectiveness and accessibility.

Firstly, the theme was inspired by Alan Turing. It made sense to set the game as though it were happening in Station X (Bletchley Park) during World War Two because, alongside the setting's intrinsic theme of spy craft, Turing's groundbreaking work on cracking the Enigma code is an incredible example of mathematics in action, showcasing its real-world impact and significance. Additionally, setting the escape room in an office made it completely transportable. As long as I have a desk and a chair, the "room" can be set up anywhere - from a theatre to a broom cupboard (see Figure 1).

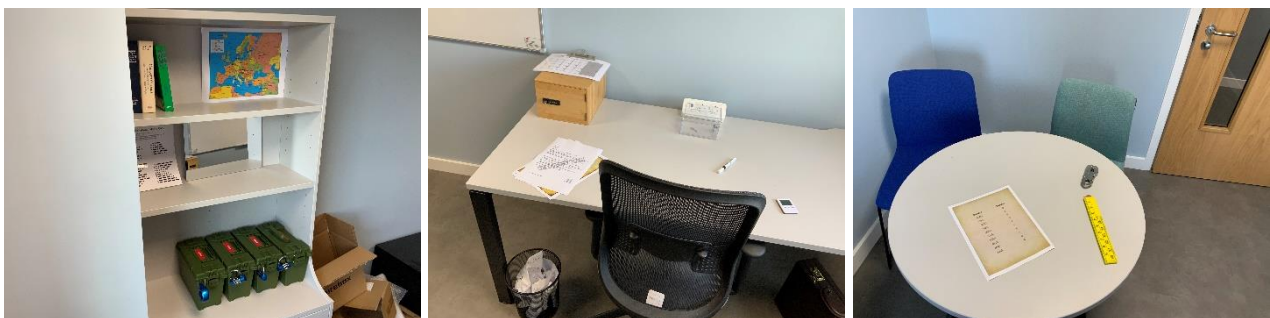


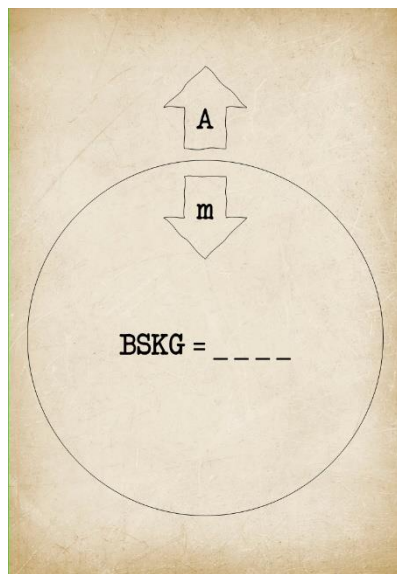
Figure 1. Basic setup of the escape room.

The activities, which include using Morse code and breaking ciphers, were designed to reflect a World War Two setting, enhancing the players' immersion in the game. Written materials were aged, and typewriter fonts were used to provide a sense of authenticity (see Figure 2). While these details

may seem minor, they contribute significantly to telling the story of the escape room and creating an engaging experience.

Accessibility was a top priority. To ensure inclusivity, apart from the initial “confidential letter”, which sets up the theme, I minimised text during the puzzles and relied heavily on iconography wherever possible (see Figure 2(a)). This approach reduced language barriers and made the puzzles more engaging and intuitive.

As mentioned, no prior mathematical knowledge was required, making the game accessible to participants with varying levels of expertise. For example, there are puzzles that depend on knowledge of Morse code and binary numbers (see Figure 2). To help the participants there are posters presented around the room that provide direct translations (e.g. from binary code to base 10 numbers, see Figure 1), thus, instead of testing their (potentially non-existent) knowledge of binary coding their powers of observations and pattern recognition are being tested.



(a)



(b)

Figure 2. Examples of aged props used in the escape room.

Transportability was another key consideration. The game was designed to be portable, with all equipment fitting into a large wheel-based case (See Figure 3). This flexibility allowed the escape room to be set up in diverse locations. Maintenance was streamlined by using modular components and off-the-shelf items, keeping costs manageable at around £400 per kit. The modular design also facilitated quick resetting between sessions, enabling multiple runs in a single day.

Technology is often a weak point in outreach scenarios. To keep technology requirements minimal, I opted for simple mechanical locks and physical props. This choice ensured reliability and reduced the risk of technical malfunctions. Moreover, the props could easily be fixed or replaced cheaply if needed.

Finally, safety was paramount; a Games Master is always present, and participants are never actually locked in. Moreover, the Games Master plays an important role in managing the engagement of the game's players. For example, they can encourage ideas from those who seem

disengaged and guide them to follow a separate path to solving puzzles. Equally, they can support a stymied team, by encouraging thoughts from the team, without explicitly providing a solution.

To provide a suitable climax and a “ticking-clock” element to the proceedings, I use a transparent post-box (see Figure 4). The start of the escape room is signified by the clock being started and the clock being posted into the post-box. The elapsed time can then be viewed throughout the challenge. The room ends once the last key is found, which opens the post-box, and the team stops the clock. These clear start and end points provide structure and an immutable “final score” of the team's performance.



Figure 3. The entire set of escape room props fits into one wheel-based case.

Unfortunately, capacity is a fundamental limitation of escape rooms. The room's capacity is limited to 1–8 participants per session, with each session lasting approximately an hour. While this limitation is partially mitigated by having four kits available, enabling up to 32 participants to play simultaneously, scaling up further would require additional resources such as multiple trained Games Masters and more funding to purchase more equipment.



Figure 4. The transparent post-box and timer, used to start and end the escape room.

Another potential solution for scaling up the reach of the escape room is to develop a digital version of the puzzles. Creating such an online platform would require additional funding to support app development and programming expertise. While a digital format would undoubtedly increase accessibility and reach, it risks losing key elements of the experience, such as the hands-on, tactile interaction and the collaborative, in-person teamwork that are central to the room's educational and engagement value.

4. Puzzle design principles

Designing the puzzles required careful thought to balance challenge and accessibility. Each puzzle was crafted to be engaging yet solvable, avoiding unnecessary complexity. To accommodate diverse skill sets, the puzzles varied in type, including logical deductions, spatial reasoning, and pattern recognition. Critically, no knowledge is assumed, thus, although there are questions that involve European geography and binary numbers, there are maps and posters that are hung around the room, which can be used to interpret the questions into solutions. This allows all students to be on the same footing initially, because all the answers are "visible", it simply comes down to who can put the building blocks together in a logical way.

When designing puzzles, my golden rule was, "do not try to be clever". The enjoyment of a puzzle lies in its solving. What feels like a logical leap for one person can be baffling for another. Equally, none of the clues are purposefully misleading or red herrings. The goal is not to fool participants or make them feel inadequate. Instead, every suggestion, even incorrect ones, should be encouraged by the Games Master, with the hopes of building the correct answer. Intentionally leading participants down the wrong logical path benefits no one.

One key principle was ensuring that each puzzle had a clear purpose and outcome. Keys and codes were used only once and had obvious applications, reducing the likelihood of confusion. Moreover, although several combination padlocks are used, they each require a different number of numbers, or letters, ensuring that each padlock clearly links to a given solution.

Most challenges were designed as single-step puzzles, following the structure "Problem → Solution → Problem". However, towards the end of the escape room, multiple-component problems were introduced, requiring input from several previous solutions. These multi-component problems were carefully scaffolded to ensure that participants knew which solutions corresponded to which questions. Moreover, these intermediate successes kept participants motivated, providing them with a sense of progress while building anticipation for the final payoff.

To ensure that no one person could monopolise solving the problems, the escape room was designed with two initial routes that could be used to progress the challenges. By splitting into subteams, no participant should be left without something to do, or a meaningful way to contribute.

5. Evaluation

The escape room has been tested with over a hundred adults, undergraduates, graduates, and secondary school children. Feedback from all groups has been overwhelmingly positive, highlighting its ability to engage and challenge participants across a wide range of ages and backgrounds.

Comments from Cathays High School students include:

- “It was really hard, but I think it showed us how to be smart and patient”,
- “I thought it was fun and quite tricky as well”,
- “It was very entertaining!”.

A teacher from Mary Immaculate High School also said, “the escape rooms activity was fantastic and my group thoroughly enjoyed [it]”.

Graduate students also reported strong engagement:

- “It was really collaborative, it felt like we were all involved the whole way through. The puzzles were fun to solve as well, it was an engaging way to deliver maths”,
- “The puzzles in the room were well thought out and encouraged our group to collaborate together well. Overall, it was a very enjoyable experience that had been put together with good care and attention to detail.”

Finally, the escape room was used as part of a Cardiff University Summer School focused on supporting students with autism spectrum conditions. Amongst all the activities that were done during the week, two participants said their favourite part of the Summer School was the escape room, with one specifying that they liked it because it “was a group effort”. This feedback demonstrates the room’s versatility and its capacity to create an inclusive environment regardless of learning needs.

A video showcasing the engagement that can be generated from running four rooms simultaneously can be viewed on Instagram at bit.ly/CardiffEscapeRoom.

Notably, these responses highlight more than just enjoyment; they point to the deeper educational impact of the escape room format. Teachers and students alike reported enhanced motivation, a willingness to persist through difficult problems, and a heightened sense of collaborative learning. Importantly, the structure of the escape room dissolves traditional hierarchies of expertise. Rather than privileging those with prior mathematical training, it invites all participants to contribute through observation, logic, and reasoning. In doing so, the activity reframes difficult mathematics as a collective challenge rather than an individual obstacle, promoting a more inclusive and resilient problem-solving mindset.

Initial observations led to minor adjustments after some early test sessions. The adjustments included replacing Bluetooth speakers with push-button sound effects and swapping fragile 3D-printed props for easily replaceable paper versions. These changes have improved both reliability and cost-effectiveness. Importantly, these refinements demonstrate that escape rooms are adaptable and can evolve with feedback.

6. Conclusion

Creating this escape room has been an immensely rewarding journey, blending my passion for puzzles with my commitment to inspiring future mathematicians. It has demonstrated that mathematics is not just a subject confined to the pages of a textbook but is alive, dynamic, and filled with creativity and teamwork. Through this project, I have observed participants from all backgrounds engage, collaborate, and discover the joy of problem-solving in ways they may never have experienced before.

If this has sparked your curiosity, I encourage you to consider creating your own escape room. It is a powerful way to connect with students, showcase the creative side of mathematics, and inspire a lifelong love for learning. If you would like tips, ideas, or more information, I would love to help. Feel free to contact me at woolleyt1@cardiff.ac.uk. All the resources, including puzzle designs, setup guides, and templates, are freely available online at bit.ly/EscapeRoomMaterial.

Together, let us work to inspire the next generation of problem-solvers and mathematicians.

7. References

Fotaris, P. & Mastoras, T., 2019. Escape rooms for learning: A systematic review. *Proceedings of the European Conference on Games Based Learning*, Volume 31, p. 235–243. <https://doi.org/10.34190/GBL.19.179>

Taraldsen, L. H. et al., 2022. A review on use of escape rooms in education—touching the void. *Education Inquiry*, Volume 13(2), p. 169–184. <https://doi.org/10.1080/20004508.2020.1860284>

Veldkamp, A., van de Grint, L., Knippels, M. C. P. J. & van Joolingen, W. R., 2020. Escape education: A systematic review on escape rooms in education. *Educational Research Review*, Volume 31, p. 100364. <https://doi.org/10.1016/j.edurev.2020.100364>

Appendix A: Equipment list

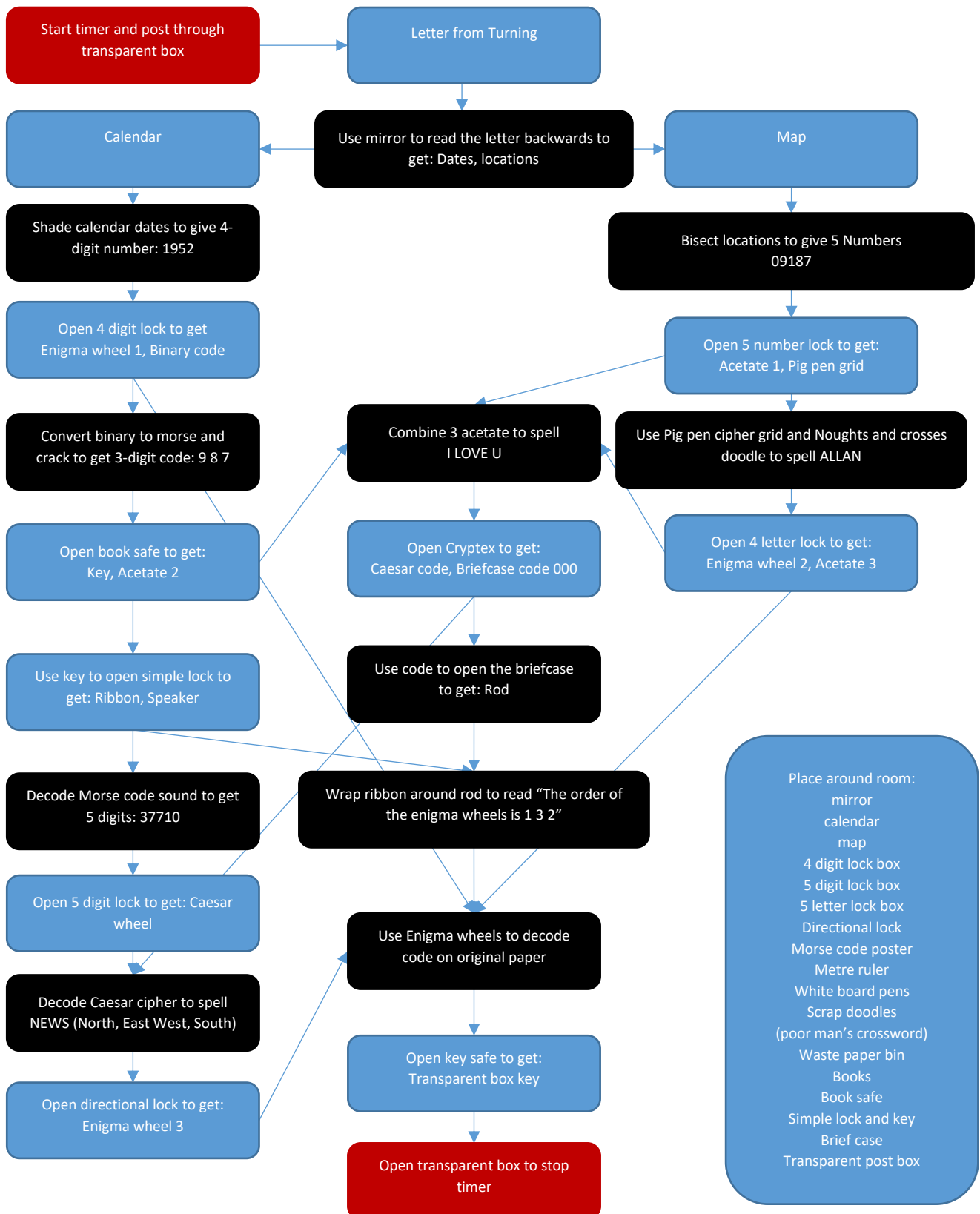
Below is a list of equipment required to run the escape room. Wherever the object can be made, or printed you will find templates in the online files, bit.ly/EscapeRoomMaterial. Moreover, many objects that I have suggested should be bought can usually be found for free, e.g. wastepaper bin. Finally, it is suggested that white board markers be provided and any paper materials are laminated to preserve them, since they often get written on.

Item	Make (M) or Buy (B)	Comment
3 Enigma wheels	M	Initially, 3D printed but can be made from paper.
3-digit book safe	B	
4-digit lock	B	
5-digit lock	B	
5-letter lock	B	
Item	Make or Buy	Comment

3 pages of acetate	B	
Binary code poster	M	
Briefcase	B	
Caesar wheel	B	Initially, 3D printed but can be made from paper.
Cryptex	B	
Directional lock	B	
Doodles	M	These are added to fill the bin, so it is not obviously an empty prop.
Key safe	B	
Lock and key box	B	
Map of Europe	M	
Mirror	B	
Morse code poster	M	
Opening letter	M	
Other general books	B	These are to place around the book safe, for obfuscation.
Pig pen cipher grid	M	Initially, 3D printed but can be made from paper.
Ribbon	B	For wrapping around the wooden rod.
Sound button	B	Plays Morse code when pressed. The Morse code sound file is given in the online resources.
Thin timer	B	
Transparent post box	B	
Wastepaper bin	B	
Wipeable calendar	M	
Wooden rod	B	

Appendix B: Solution structure

If you are interested in planning your own escape room I found it most useful to plan the “shape”, or structure of the room first on paper. Namely, the challenges (coded blue) and solutions (coded black) are mapped by arrows to highlight how each puzzle relies on the rest.



THIS PAGE
DELIBERATELY
LEFT BLANK

CASE STUDY

Implementing Active Learning in Undergraduate Mathematics Using Tarsia Puzzles

Francis Duah, Mathematics Department, Toronto Metropolitan University, Toronto, Canada, Email: f.duah@torontomu.ca

Boza Tasic, Ted Rogers School of Management, Toronto Metropolitan University, Toronto, Canada, Email: btasic@torontomu.ca

Abstract

Active learning is a pedagogical approach that emphasizes student engagement and participation in the learning process. One innovative tool that has shown promise in facilitating active learning in mathematics is Tarsia, a software for creating jigsaw-style puzzles. This paper describes the design and implementation of Tarsia puzzles used in a tutorial for a first-year calculus course for engineering students, where participation was optional. It also highlights their potential to enhance conceptual understanding, foster collaboration, and increase student motivation.

Keywords: active learning, puzzles, calculus, collaboration, student engagement.

1. Introduction

Undergraduate mathematics education has long grappled with the challenge of engaging students in meaningful learning activities. Despite the pervasive presence of technology in all walks of life, mathematics teaching methods have not changed significantly within the last half-century. Although traditional mathematics pedagogy is often characterized by passive reception of information and may fail to stimulate student interest or promote deep understanding, it remains ubiquitous across all levels of education, from K-12 to higher education. Mathematics education research consistently advocates for progressive, evidence-based teaching methods that emphasize active learning strategies.

The term “active learning” is used to describe “classroom [teaching] practices that engage students in activities such as reading, writing, discussion, or problem solving, that promote higher-order thinking” (Conference Board of the Mathematical Sciences, 2016) (p. 1). This definition focuses on what students do rather than what the teacher does. Thus, active learning is student-centred rather than teacher centred.

In their paper entitled, “What does Active Learning Mean for Mathematicians?”, Braun et al. (2017) suggested some strategies for implementing active learning in the classroom. Some of these strategies relate to the learning environment, while others focus on the design of learning tasks. Some examples of active learning strategies in the literature are think-pair-share, use of classroom response systems, puzzles and games, flipped classroom, inquiry-based learning, modelling in computer laboratories, and writing (Braun et al., 2017; Rosenthal, 1995). TACTivities (tactile activities) are group-based, hands-on learning tasks that promote engagement, collaboration, communication, and critical thinking. They are low-tech manually created resources such as card matching, dominoes, and placement cards as described by Hodge et al. (2020). As such, TACTivities can be beneficial in promoting both mathematical thinking and communication skills.

Active learning strategies which engage students in critical thinking appear to offer a promising alternative to the traditional mathematics pedagogy. Among these strategies, the use of Tarsia

puzzles has emerged as an effective tool for active learning in mathematics education. Tarsia puzzles are generalized domino-like activities, created using specialized software. The puzzles range from traditional dominoes to more complicated jigsaw puzzles, as well as follow me and matching cards. Digital format allows for quick updates and re-purposing of puzzle content, producing outcomes that are generally more challenging than manually created TACTivities. While TACTivities, as described by Hodge et al. (2020) rely on physical material and manual creation, Tarsia puzzles offer a digitally enhanced alternative that preserves tactile engagement while enabling greater scalability and content complexity.

This paper describes the design and implementation of Tarsia puzzles and their use at Toronto Metropolitan University (TMU) in a tutorial for a first-year calculus course for engineering students, where participation was optional. It also highlights the potential of Tarsia puzzles to enhance conceptual understanding, foster collaboration, and increase student motivation.

In the next section, we provide a brief description of the extant literature on the efficacy of active learning in mathematics education.

2. Research on Active Learning

Research on active learning in undergraduate mathematics has grown over the last two decades (Duran et al., 2024; Freeman et al., 2014; Lugosi & Uribe, 2022; Stanberry, 2018; Theobald et al., 2020). Freeman et al. (2014) conducted a meta-analysis of 225 studies on active learning. They found evidence that active learning was more effective when coupled with course examinations that “are designed to diagnose known misconceptions, in contrast to [those] that emphasize content mastery or the ability to solve quantitative problems” (p. 8411). Establishing effectiveness of active learning is difficult because the effect could be attributed to either student gaining better understanding of the material due to the active learning strategies used, or instructors teaching to the test. Examinations in mathematics classes continue to reward speed and accuracy and are typically insensitive to the quality of a student’s understanding.

Some of the research on active learning has explored the efficacy of active learning on achievement gaps experienced by underrepresented and marginalized students in STEM disciplines. For example, Theobald et al. (2020) tested the hypothesis that underrepresented and marginalized students in active-learning classes experience narrower achievement gaps than those in traditional lecturing classrooms, averaged across all STEM fields and courses. They found that on average active learning worked to narrow such achievement gaps. However, they cautioned that the effect size was highly dependent on the extent to which students were engrossed in active learning activities and that in some cases “...active learning increased achievement gaps instead of ameliorating them,” (p. 6479). The prevalence of group interactions in active learning activities makes it incumbent upon instructors to be mindful of the impact of social dynamics on students’ experiences of those activities, especially when those students belong to groups that have historically been underrepresented or marginalized in the field of mathematics.

Active learning, when carefully designed, can increase students’ grades, attendance and engagement in classes. Duran et al. (2024) found that students in calculus classes that employed active learning had higher grades than those in lecture-based calculus classes, after controlling for attitudes towards mathematics and various demographics. Stanberry (2018), reflecting on a redesign of a calculus course to employ active learning as a new pedagogical strategy, observed increased student attendance and engagement in classes.

3. Active Learning Classroom at TMU

An active learning classroom (ALC) at TMU was designed for instructors to try new learning strategies with their students and share the experiences with the TMU community. Figures 1 and 2 depict two different configurations of the ALC space.

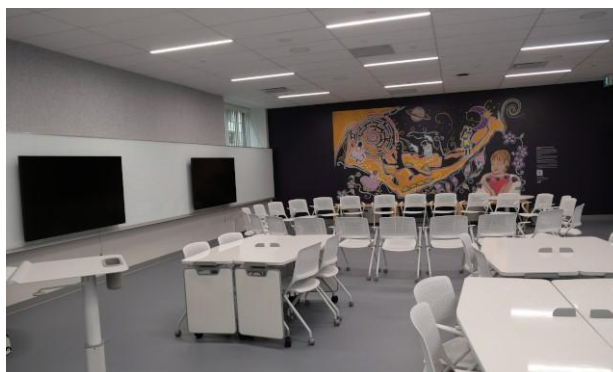


Figure 1: Active learning classroom at Toronto Metropolitan University



Figure 2: Active learning classroom at Toronto Metropolitan University

During the Winter 2024 semester, the first author used this classroom for 8 weeks to pilot two active learning strategies in a first-year calculus course for 1400 engineering students divided into several sections. This course has scheduled weekly lectures and labs which students are expected to attend. In addition to these, a tutorial with optional attendance was introduced to promote active learning using Board Rounds and Tarsia puzzles. These tutorial sessions were run on Fridays from 4:00 – 6:00 pm and considering that they were not on students' schedules we did not expect a high turnout. On average 15 students attended these sessions, with the maximum attendance of 30 and the minimum of 10 students. There was a core group of 10 students who never missed these sessions.

Board Rounds involved groups of 3 to 5 students who worked on solving problems written on boards on the walls in the classroom or on the tops of desks which were whiteboards.

Tarsia puzzles are akin to dominoes. These puzzles were created using a software known as Tarsia Formulator. In the next section we describe the software and how the puzzles were designed and implemented.

4. Implementing Tarsia Puzzles in Calculus

4.1 Tarsia Puzzle Software

Tarsia Formulator is a puzzle generating software that was created by Hermitech Laboratory (<http://www.mmlsoft.com/index.php/products/tarsia>). The software has a free license and requires Windows operating system to work. The software, while it could be used in any discipline, was originally created to support mathematics teachers. Although the software has been extensively used for primary to post-16 mathematics, particularly in the UK, it has rarely been used to create puzzles for university mathematics teaching.

The Tarsia software enables teachers to create mathematics puzzles that require students to identify where logical links exist between the teacher-defined mathematical objects or terms. Students match pieces together to establish these logical links in a way akin to dominoes. In addition, it also enables instructors to customize their puzzles to the needs of their students and to their teaching style.

To create effective puzzles, the mathematical objects or terms used need to be clear and simple to enable establishing the logical links. In addition, the following factors need to be considered:

- *Alignment of Puzzle Activities with Learning Outcomes:* Puzzles should be designed to align with the specific learning outcomes of the topic the puzzles are based on. This ensures that the activity reinforces key concepts and skills that students need to understand and acquire.
- *Clear Instructions and Support:* Clear instructions and appropriate scaffolding are essential for successful implementation. Instructors should include pieces with logical links, starting with concepts most familiar to students and progressing to concepts that have been introduced to them more recently. Instructors should explain the purpose of the puzzle and provide guidance as needed to help students stay on track.
- *Allow Time for Reflection and Discussion:* When students complete solving the puzzle instructors should bring students together to reflect on the activity. This can include reviewing the solutions, discussing strategies used, and addressing any misconceptions that arose during the activity.

The software has a user-friendly interface that enables point and click. Creating a single puzzle takes as little time as 30 minutes, even for someone new to the software.

One thing we learned about the use of the software is that the formatting of equations needs to be checked before printing. For example, we know trig functions need not be italicized. However, even with the best of efforts, sometimes, the formatting reverts to italicization.

The puzzles that were used during the tutorial fostered mathematical discourse. The reason for this is because of the deliberate choice of elementary integrals and series as puzzle theme. Our idea was to start with simple examples that can be solved without paper and progress towards more complicated ones. The first author who facilitated the tutorial sessions used question and answer approach to provide a scaffold to the students to enable them to make links between puzzle pieces. In this sense, the first author acted as the “knowledgeable other” in facilitating learning (Vygotsky, 1978). The discussions that ensued enabled the students to address misconceptions they might have had.

4.2 A sample of Tarsia Puzzles used in class

Three examples of Tarsia puzzles that we used during the tutorial sessions are shown in Figures 3, 4 and 5.

Figure 3 depicts the Tarsia puzzle based on the topic Integration. The chosen integrals were elementary and could be solved by inspection only. Students were expected not to write on paper but rather to engage in a discussion that will eventually lead them to match pieces of triangles with logical links between them.

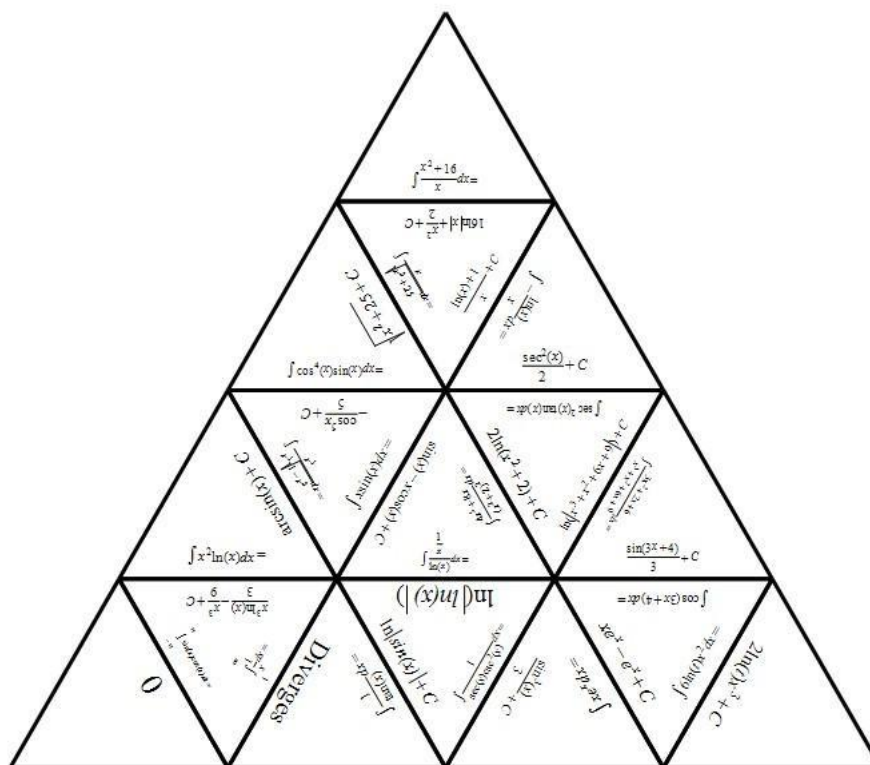


Figure 3: Integration techniques puzzle

The classical domino-looking Tarsia puzzle depicted in Figure 4 was based on the topic Series. The mathematics objects and/or terminologies with logical links were chosen to enable the students to consolidate their knowledge of series and their behaviour.

					Start
					e^x
$a_n = \frac{n^3 + 5}{n + 2}$	Convergent	$\sum_{n=1}^{\infty} \left(\frac{1}{\sqrt[3]{n^4}} \right)$	$a_n = (-1)^n n$	Not Monotonic	$\sum_{n=0}^{\infty} \frac{x^n}{n!} =$
Increasing Sequence					
$\sum_{n=1}^{\infty} \left(\frac{1}{n} - \frac{1}{n+1} \right) =$					
1	$a_n = \frac{1}{2n^2 + 1}$	Decreasing Sequence	$\sum_{n=1}^{\infty} \left(\frac{3}{2} \right)^{n-1}$	Divergent	Finish

Figure 4: Series puzzle

Figure 4 depicts the Tarsia puzzle on a mix of topics: series, functions of several variables, and partial derivatives. The puzzle was used in a session just before the final exam and was created for students to consolidate their knowledge of the material we believed students found difficult.

The following is the link to [Tarsia puzzles](#).

We observed that the puzzle in Figure , which is a classical domino-style puzzle on series, was the least challenging one for the students. This may have to do with familiarity with classical dominoes. The next challenging puzzle is the one in Figure on integration. We intentionally picked up Elementary Integrals as a theme for this puzzle so that students could engage in completing the puzzle by discussing the links rather than having to compute integrals on paper. Finally, the puzzle in Figure was the most challenging one because it was on mixed topics and included two different geometric shapes of puzzles.

In the next section, we reflect on the learning experience from our point of view as instructors and suggest future directions for research on active learning in undergraduate mathematics using the Tarsia puzzles.

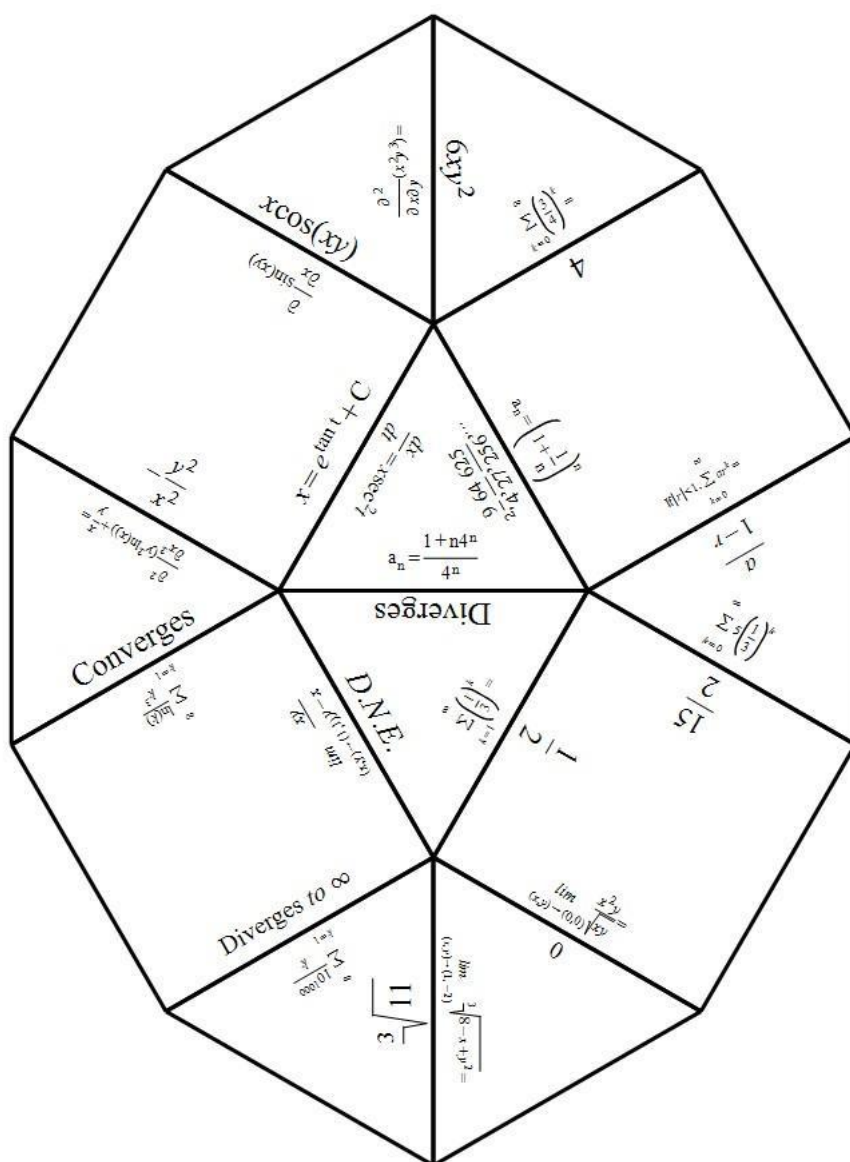


Figure 5: Mixed topic puzzle

5. Reflection, Future Research and Conclusion

This case study was not empirical research. Our intention was to try out the Tarsia puzzles and to get informal feedback from the students, as well as to ascertain the number of students who would participate in this activity. We consider this intervention as a pilot that will be followed up with a full-scale research study with the Research Ethics Board approval.

A number of observations were made during these tutorial sessions, and we grouped them into three themes: enhanced understanding, collaboration, and increased motivation and engagement.

Enhanced Understanding: Tarsia puzzles enable students to engage in discussions about mathematical objects, expressions, equations, terms and terminologies and to deduce the logical connections between them. By actively engaging in discussions about the logical links between mathematical objects, expressions, equations, terms and terminologies and seeking correct matches between pieces of the Tarsia puzzle, students reinforce and consolidate their understanding of the mathematical content they have learned. This active engagement promotes deeper comprehension compared to passive listening or rote memorization (Prince, 2004). When these tutorial sessions were scheduled, the initial thought was that perhaps 1 or 2 students will show up on Friday afternoon from 4 pm to 6 pm. Surprisingly, there was a good attendance every week. It is tempting to suggest that the students who attended were those who were highly motivated. However, after 8 weeks, the first author came to know almost all students who attended. We believe that students came to the tutorial sessions because the kind of activities they were doing, including the Tarsia puzzles, were different from what they would normally do in labs. Lab questions are usually routine textbook exercises, and for these exercises students have to write their own solutions. However, with the Board rounds and the Tarsia puzzles, students worked together and more importantly engaged in discussions and communications about mathematical ideas.

Collaboration: While the Tarsia puzzles can be solved individually, we observed that when solved in pairs or small groups, collaboration can be fostered among students through their discussion and conferring and explaining why logical links exist between pieces. As they discuss potential matches and strategies, students articulate their reasoning and learn from each other. This collaborative environment enhances communication skills and promotes a deeper learning and understanding (Johnson et al., 1998).

Increased Motivation and Engagement: The game-like nature of Tarsia puzzles makes learning more enjoyable. The challenge of completing the puzzle provides a sense of achievement and can motivate students to persist in solving complex problems. This increased engagement can lead to a more positive attitude towards mathematics and greater overall participation in the classroom (Freeman et al., 2014).

The Tarsia puzzles used in the tutorial sessions were physical samples. However, we envision the development of a mobile or web-based app that could simulate the puzzle experience. Such an app would allow these activities to be used in a large lecture setting or on the move, addressing some of the limitations associated with traditional TACTivities. Implementing active learning in the classroom could be challenging, particularly in a large lecture. In labs, where attendance is expected and class sizes are typically below 50, it is more feasible to incorporate active learning strategies. Future experimental research could examine the effectiveness of Tarsia puzzles in promoting engagement and conceptual understanding in mathematics education.

6. References

- Braun, B., Bremser, P., Duval, A. M., Lockwood, E., & White, D. (2017). What does active learning mean for mathematicians. *Notices of the AMS*, 64(2), 124–129.
- Conference Board of the Mathematical Sciences (2016). Active learning of in post-secondary mathematics education.
- Duran, P. A., Castillo, A. J., Watson, C., Fuller, E., Potvin, G., & Kramer, L. H. (2024). Student attitudes and achievement in active learning calculus. *International Journal of Mathematical Education in Science and Technology*, 55 (3), 759–780.
- Eison, J. (2010). Using active learning instructional strategies to create excitement and enhance learning. *Active Learning*, 2(1), 1–10.
- Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23), 8410–8415.
- Hermitech Laboratory (n.d.). Information on Formulator Tarsia. Retrived from <http://www.mmlsoft.com/index.php/products/tarsia>
- Hodge, A., Wanek, K., & Rech, J. (2020). TACTivities: A Tactile Way to Learn Interdisciplinary Communication Skills. *PRIMUS*, 30 (2), 160-171. <https://doi.org/10.1080/10511970.2018.1532937>
- Johnson, D. W., Johnson, R. T., & Smith, K. A. (1998). Cooperative learning returns to college: What evidence is there that it works? *Change: The Magazine of Higher Learning*, 30 (4), 26-35.
- Lugosi, E. & Uribe, G. (2022). Active learning strategies with positive effects on students' achievements in undergraduate mathematics education. *International Journal of Mathematical Education in Science and Technology*, 53 (2), 403–424.
- Prince, M. (2004). Does active learning work? A review of the research. *Journal of Engineering Education*, 93(3), 223–231.
- Rosenthal, J. S. (1995). Active learning strategies in advanced mathematics classes. *Studies in Higher Education*, 20(2), 223–228. <https://doi.org/10.1080/03075079512331381723>
- Stanberry, M. L. (2018). Active learning: A case study of student engagement in college calculus. *International Journal of Mathematical Education in Science and Technology*, 49 (6), 959–969.
- Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., ... & Freeman, S. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. *Proceedings of the National Academy of Sciences*, 117(12), 6476-6483.
- Vygotsky, L. (1978). Mind and society: Interaction between learning and development, (pp. 79–91). Cambridge, MA: Harvard University Press.

THIS PAGE
DELIBERATELY
LEFT BLANK

WORKSHOP REPORT

Diversity and Decolonisation in Mathematics

Siri Chongchitnan, Warwick Mathematics Institute, University of Warwick, Coventry, UK.

Email: Siri.Chongchitnan@warwick.ac.uk

Ryan L. Acosta Babb, Warwick Mathematics Institute, University of Warwick, Coventry, UK.

Email: Ryan.L.Acosta-Babb@warwick.ac.uk

Jonathan Skipp, Department of Mathematics, College of Engineering and Physical Sciences, Aston University, Birmingham, UK. Email: J.Skipp@aston.ac.uk

Helena Verrill, Warwick Mathematics Institute, University of Warwick, Coventry, UK.

Email: H.A.Verrill@warwick.ac.uk

Elliot M. R. Vincent, Warwick Mathematics Institute, University of Warwick, Coventry, UK.

Email: E.Vincent@warwick.ac.uk

Abstract

The 'Diversity and Decolonisation in Mathematics' conference took place at the University of Warwick Mathematics Institute on 24-25 April 2025. This report highlights the main themes and key messages of the conference.

Keywords: inclusivity, diversity, decolonisation

1. Motivation and aims

Over the past few years, equality, diversity and inclusion (EDI) issues in academia have gained attention within the mathematics community. On the one hand, there have been pioneering, progressive efforts to discuss diversity and decolonisation issues in mathematics, particularly around university mathematics curriculums. On the other hand, diversity and decolonisation have sometimes been brushed aside as irrelevant (*how can Pythagoras' Theorem be racist?*) or politicised as another woke agenda gone too far.

We the conference organisers believe that there is a need for like-minded mathematics academics to come together in a safe space to share ideas on how diversity and decolonisation can make mathematics a richer, more inclusive subject to study and do research in.

The '*Diversity and Decolonisation in Mathematics*' conference¹ took place at the Warwick Mathematics Institute on 24th and 25th April 2025, hosting over 50 academics from 23 universities from UK and abroad. The conference focussed on two broad areas:

1. **Decolonising the mathematics curriculum**, including a) conducting an open discussion of the meaning and legacy of colonisation in the academic context, b) teaching mathematics and its history in a non-Eurocentric framework, c) diversifying the university maths curriculum to acknowledge the work of non-European mathematicians.

¹ <https://warwick.ac.uk/fac/sci/math/general/outreach/diversity-decolonisation-conference-2025/>

2. **Diversity issues in mathematics**, including a) lived experiences and mathematical contributions of mathematicians from diverse ethnicities, genders, sexual orientations and socio-economics backgrounds, b) making university mathematics more inclusive for neurodivergent and disabled students.

This report summarises the contributions shared at the conference and highlights key take-away messages. This document was prepared by the organisers of the conference (Chongchitnan, Acosta Babb, Verrill and Vincent) with contribution from a conference participant (Skipp).

2. Contributions

The conference opened with a brief welcome from the Chair (Chongchitnan) and Megan Caulfield, a representative of Warwick University's Student Office, which funded the event. Ms Caulfield highlighted key achievements of a 3-year plan for Inclusive Education¹ at Warwick, of which this conference is a key part.

2.1 Decolonising mathematics

Catarina Carvalho (Hertfordshire) kicked off the conference by defining colonisation as the practice of domination, which involves the subjugation of one people to another, and dismissing ideas that do not conform to white European traditions. She challenged the notion that decolonisation is irrelevant for mathematics and gave examples of how colonisation ideologies gave rise to inequitable, unethical and racist practices that still exist in higher education. To encourage student buy-in, Dr. Carvalho recommended asking open-ended questions around ethics in personal tutoring groups, to stimulate students' discussion. More generally, she reported on several initiatives related to the workshop themes run by the University of Hertfordshire. This experience is collated in the Diversifying and Decolonising the University website (D'Sena et al., 2025) and podcast (Lloyd 2025), and the Diversifying and Decolonising Mathematics website (Carvalho 2023).

Finally, Dr. Carvalho discussed the rise of *data colonialism*, i.e. the exploitative practice of tech companies in extracting and analysing data for profit (Couldry & Mejias 2018), made worse in recent years with the rise of AI. She also drew attention to the environmental harm caused by intensive data processing, often at the expense of disenfranchised communities. Dr. Carvalho concluded with a powerful quote by the mathematician Kit Yates that "*if taking action is political, then so is failing to act*".

Next, Ric Crossman (Durham) discussed *QuantCrit*, a framework combining quantitative research and critical race theory (Gilborn, Warmington & Demack 2017) and its potential for decolonising mathematics. He argued that racism itself can often be regarded as a confounding variable in analysis of racial data. This understanding is important in order to avoid making false, racist claims from data.

Sue Johnston-Wilder (Warwick) rounded off the morning session by presenting the harms of colonial views of mathematics, including learner exclusion and mathematics anxiety. She discussed how such anxiety can be overcome, including adopting the African philosophy of *Ubuntu* (often translated as "*I am because we are*") into the classroom (Ngomane 2019).

¹ <https://warwick.ac.uk/services/dean-of-students-office/inclusiveeducation/>

2.2 Diversifying the curriculum

Rae Shaw (Warwick) discussed their experience of teaching mathematics to children from ages 5 to 18 in Zambia, and their research into diverse number systems used around the world (Shaw 2023). Rae explained how teaching in base 10 impacts children's ability to learn mathematics in the primary years in Zambia, given that in their native language, counting is in base 5. In many countries, mathematics education is given entirely in English, which may present a barrier to learning, and challenges our assumption that mathematics is a universal language.

Jason Ho Ming Yip (Middlesex) reported on an experimental pedagogical intervention at a school in Milton Keynes, which involved teaching mathematics alongside historical, cultural and societal insights, with biographies and anecdotes of the mathematicians involved. This humanises the topics and triggers students' curiosity. Data from the enhanced class compared with a control group showed significant improvement in the enjoyment of studying mathematics.

2.3 Diverse history of mathematics

Brigitte Stenhouse (Open) presented a number of student summer projects on a diverse range of historical mathematicians, which ties into the *Diverse History* theme of the conference.

Dr. Stenhouse worked with undergraduate interns (level 2 or 3 at the Open University) on fifteen sources which cover mathematics across five continents, and over 2000 years, and it is continuing to grow. In this project, entitled *Contextualising the Curriculum through the History of Mathematics*, students were encouraged to use "primary source material to build [their] awareness of the historical development of mathematics, from a global perspective". Dr. Stenhouse provided some case studies from the project. The case of Chike Obi in particular, created a discussion about the role of a history of mathematics: on the one hand, he was a source of inspiration for many young mathematicians, on the other, he engaged in antisemitic and authoritarian rhetoric. Hence the critical question: "What tone should be used [...] to ensure these studies aren't seen as 'celebrations' but as historical treatments of ideas and the people who had them?" The talk closed with Dr. Stenhouse reminding us that "history is not just facts and biographies, but can enable a meaningful engagement with mathematical ideas, *in context*". The resources from this project will be shared via the OpenLearn platform in the near future.

Prof. Della Dumbaugh (Richmond) explored the lives of Caroline Bamberger Fuld — a department-store magnate — and Clare Booth Luce — a playwright and activist. She made a case for their surprising influence on the development of mathematics and science in America in the twentieth century through the establishment of funds for women to study and carry out research in mathematics. These stories sparked a discussion of the funding differences between the US and European contexts.

Nicholas Jackson (Warwick) offered a re-appraisal of *Hypatia of Alexandria*, tracing the scant historical sources we have for her life and work, and warning that much of our "popular" understanding of this figure stems from later, inaccurate and fictionalised accounts. He ended his discussion with a number of thought-provoking questions, such as whether "her adoption as a role model/paragon/totem/etc. are entirely helpful" in discussions of diversity in mathematics.

Clemency Montelle (Canterbury) was scheduled to deliver the talk *Doing Mathematics Differently - An Exploration of Mathematical Practices from the Indian Subcontinent*, but was unfortunately unable to travel. Her talk aimed to discuss some of the mathematical highlights of this scientifically dynamic

tradition and account for some of the challenges faced by historians of mathematics in the task of accounting for the scientific legacy of this extensive and rich culture of inquiry.

2.4 Lived experiences

Jordan Marajh (Queen Mary) discussed Queen Mary's "*A Mathematician Like Me*" project, which produced a booklet, posters, and online resources¹ about a wide range of diverse figures in mathematics.

Nira Chamberlain (Loughborough) gave a highly motivational talk about his own experiences of overcoming prejudice to become a mathematician. He also spoke about black mathematicians generally, and how they are often overlooked in the usual discussions of the history of mathematics. Prof. Chamberlain gave many examples of important work by black mathematicians such as Francis William, Benjamin Bannekar and Euphemia Lofton Haynes, as well as prominent contemporary black mathematicians.

Michael Cavaliere (Warwick) discussed his contribution to Warwick's *Inclusive Education* project. In particular, he shared the findings from his summer project on understanding the experience of Warwick maths students with disability and neurodivergence (autism in particular). Contrary to the stereotype of "all mathematicians being a little bit autistic", maths students diagnosed with autism do often face serious barriers during their university study. He discussed what maths departments could do better to identify and accommodate disabled and neurodivergent students.

Ashleigh Ratcliffe (Leicester) spoke about the work of the Piscopia Initiative², which aims to create a community and provide support for women and under-represented genders in mathematics. She described the resources, events and projects that they run, and the aims of the initiative. She also presented what the Piscopia Initiative have learned about the current challenges facing women and under-represented genders; in terms of attracting students into PhDs, and issues these students faced during the PhD itself.

Elliot Vincent (Warwick) shared information about the QEDnetwork³, a recently launched network aimed at supporting, advocating for, and creating a community for LGBTQ+ researchers in mathematics. They raised awareness of some of the major issues currently facing LGBTQ+ people in academia and shared about historical and present-day victories which have been achieved by the advocacy of similar individuals and organisations.

Daniel Ratliff (Northumbria) discussed an upcoming project which aims to create a report on the experience of queer people working in mathematics. He presented data found in similar studies in physics and the physical sciences, which have revealed statistical and experiential inequalities in the workplace experiences of LGBTQ+ people. He emphasised the importance of collecting these data in mathematics too, so that the issues in this field can be properly identified and addressed. The report will be disseminated via the QEDnetwork website.

¹ <https://www.qmul.ac.uk/maths/our-community/equality-diversity-and-inclusion/a-mathematician-like-me/>

² <https://piscopia.co.uk/>

³ <https://sites.google.com/view/qednetwork/home>

2.5 Sharing teaching practices, interventions, and resources

Many speakers at the workshop shared examples of specific practices, courses, and interventions in which they topics relevant to this workshop into mathematics teaching, and resources that the community at large can draw on to make similar interventions.

Andrew Potter (Open) reported on the development of an Inclusive Curriculum Tool, designed to assist the review of STEM curricula at the Open University, with the aim of informing revisions, as part of the Open University's Access and Participation Plan. The tool consists of a series of prompts, used by Associate Lecturer reviewers to critically examine distance learning materials. For example, reviewers are invited to enquire whether the materials reflect the diversity of characteristics of students and society more generally, whether they are fully inclusive and intersectional, whether colonial views are highlighted and challenged, etc. Themes identified during the reviews were collated and the work integrated into a 'staircase' model of inclusivity. The development and use of the Inclusive Curriculum Tool is described in Veuger et al (2023).

Martyn Parker (Warwick) presented an initiative at the Department of Statistics wherein students were recruited to co-create projects around decolonisation and inclusion, specifically within the Statistics department. This initiative was launched to address the lack of specific, actionable examples of decolonisation and inclusion within a mathematical Higher Education department. The projects resulted in action plans implemented by the Department of Statistics to increase student engagement, support and community-building, as well as curriculum and assessment changes. The framework for these co-creation projects will be released publicly later this year. Readers should look out for a collection of co-creation projects on the Warwick Statistics website.

The workshop closed with a colloquium *Encouraging Diversity while Teaching the History of Maths and Society*, given by Peter Rowlett (Sheffield Hallam). He recounted his experience teaching History of Mathematics, and Maths and Society content over nine years. His teaching approach is centred around examining the context in which mathematics has and is being created and used. Dr. Rowlett gave examples of topics taught in his courses, including a) how myths and storytelling in mathematics could lead to a narrow view of how it is created, b) who gets to be a mathematician, c) bias in AI technology which can present a distorted view of history as unrealistically diverse. He outlined how assessment is carried out by means of small-group projects on topics chosen by students and shared some findings of these projects. Dr. Rowlett's reflections on his approach are presented in Rowlett (2025).

3. Feedback and future directions

3.1 Feedback

After the event, a feedback form was sent to all those who registered, with three questions. An additional question then allowed respondents to identify themselves with their name and email address. We received feedback from 16 respondents. Of these, 11 chose to identify themselves; 10 of whom attended the conference, and 1 who was unable to attend.

Q1 Tell us something positive about the event. (e.g. the most impactful talk? the most memorable experience?)

The three most common themes throughout these responses were: the sharing of ideas; space to engage in constructive discussion and problem solving; and the range and depth of content that was covered.

Many respondents benefited from the sharing of tangible resources (e.g. books, course material), in addition to ideas and experiences. Hearing about the challenges other institutions have encountered, as well as the relative challenges and successes of initiatives and course content that have been trialled, is something that attendees found valuable to take away and reflect on in their own institutions.

Many responses also reflected positively on the space to have thoughtful and challenging discussions about the issues in question. Several expressed that they felt the conference provided a safe opportunity to express constructive criticism and challenges within the topics of diversity and decolonisation, while working towards solutions.

Finally, many also appreciated that the programme covered a wide range of content. This was both with respect to the identities/themes covered by the talks, or with respect to the area of work (teaching, practice, research). One respondent felt that the conference benefited from the fact that speakers were able to assume both prior knowledge of, and belief in the importance of diversity issues. They felt that this allowed for discussions to go deeper than they are often able to in more general settings.

Q2 Tell us how we could do better for the next event. (e.g. more talks? longer conference? more specialised scope?)

The most major suggestion from respondents was that explicit space for a roundtable discussion would have been beneficial. Some felt that they would have liked such a space to discuss how these initiatives and ideas could be expanded within departments, or implemented into curriculums; while others mentioned this in the context of feeling like many discussions spilled over into break- and lunch-times, and thus were a little more constrained.

Q3 Any other comments? (e.g. what impact will the conference have on your institution? should this conference to take place annually? how could your institution contribute?)

Every respondent either explicitly or implicitly endorsed the suggestion that this conference should happen annually or at least happen again. Notably, 8 of the 16 respondents expressed an interest in helping to host, organise, or contribute to a future iteration.

Five respondents noted that they have shared, or intend to share, a report about the conference with relevant members of staff at their institution (EDI lead, Head of Department etc), and one additional person who was unable to attend the conference also reached out to the organisers to say that they would be very interested in circulating a report on the conference.

Five respondents also said that they have gained concrete 'take-away's from the conference either in the form of new ideas for teaching material, or new awareness of initiatives and resources that they can share with students and colleagues.

3.2 Discussion and Future directions

A major outcome of the conference was the chance for participants to share resources, initiatives, and ideas for course content. Having the dedicated space to discuss challenges that have been encountered and ideas that have been trialled in different institutions has the potential to prevent the duplication of effort nationally. This is especially important since much of the EDI and decolonisation work in each institution is voluntary and taken on out of personal desire. Providing the space for people working on these issues across institutions to share can reduce the amount of time and work that needs to be put in by the relatively small number of staff.

Overall, the feedback we received reflected a great enthusiasm for the outcomes of the conference, and for the continuation of this event on an annual basis. Many respondents voiced a willingness to help contribute to the running of future iterations of the conference and to share their experience of the conference with colleagues at their home institutions. As such, we have plans for this event to take place again next year, possibly hosted by a different institution and organising team.

4. References

Carvalho, C. (2023). Diversifying and Decolonising Mathematics website.

<https://diversifymathematics.gitlab.io/resources/>

Couldry, N., and Mejias, U. A. (2018). Data Colonialism: Rethinking Big Data's Relation to the Contemporary Subject. *Television & New Media*, 20(4), 336-349.

<https://doi.org/10.1177/1527476418796632>

D'Sena, P., de Sousa, S., Lloyd, C. et al. Diversifying and Decolonising the University website.

<https://diversifyingherts.wordpress.com/>.

Gillborn, D., Warmington, P., and Demack, S. (2017). QuantCrit: education, policy, 'Big Data' and principles for a critical race theory of statistics. *Race Ethnicity and Education*, 21(2), 158–179.

<https://doi.org/10.1080/13613324.2017.1377417>

Lloyd, C. Diversifying and Decolonising the University podcast.

<https://podverse.fm/podcast/IR2H4Ds1x>

Ngomane, M. (2019). *Everyday ubuntu: living better together, the African way*, New York, Harper Design.

Rowlett, P. (2025). Teaching history of mathematics for first year undergraduate skills development. *The Mathematical Gazette*, 109(574):86-92.

<https://doi.org/10.1017/maq.2025.13>

Shaw, R. (2023). Methods of Counting.

<https://warwick.ac.uk/fac/sci/mathsgeneral/outreach/diversity/shaw/>

Veuger, S. J., Butler, D., Wood, P., & Potter, A. (2023). Inclusive Frameworks in Online STEM Teaching and Learning. In J. Keengwe (Ed.), *Handbook of Research on Innovative Frameworks and Inclusive Models for Online Learning* (pp. 28-51). IGI Global Scientific Publishing.

<https://doi.org/10.4018/978-1-6684-9072-3.ch002>

THIS PAGE
DELIBERATELY
LEFT BLANK

WORKSHOP REPORT

Transformative Workshops Empowering International Postgraduate Students

B.K. Ashley Hoolash, Lead of the Centre for Mathematics & Statistics Teaching and Learning, Middlesex University Mauritius, Unicity, Mauritius. Email: B.Hoolash@mdx.ac.mu
Sweta Rout-Hoolash, Senior Lecturer, Department of Education, Middlesex University Mauritius, Unicity, Mauritius. Email: S.Rout-Hoolash@mdx.ac.mu

Abstract

This is a report on a series of professional development workshops organised by the Centre for Mathematics & Statistics Teaching and Learning (CeMaSTeL) in 2024 at Middlesex University Mauritius. Workshop series form an integral part of CeMaSTeL activities and have evolved to include opportunities for interdisciplinary collaboration among Middlesex University campuses (UK and Mauritius). The four principles of the university's strategy 2031 are exemplified by carefully designing the workshop themes and delivery.

Keywords: Numeracy support, Non-specialist Mathematics and Statistics students, Middlesex University strategy 2031.

1. The Evolution of CeMaSTeL – Centre for Mathematics & Statistics Teaching and Learning

At the outset it is important to first understand the context of Middlesex University Mauritius. Operating under a paradigm of transnational education (TNE), this is an international branch campus of the UK Middlesex University, a global university, with three global campuses additionally in London, UK and Dubai, UAE. In 2009, Middlesex University Mauritius became the first accredited British branch campus to open in Mauritius, primarily serving learners across Africa and the Indian Ocean region. Today, it serves as a vibrant learning hub, catering to a diverse community of over 1,600 students from across 40+ countries. Middlesex University ranks in the top 150 young universities globally (Times Higher Education rankings) and 6th in the UK.

Started in 2010, a Mathematics Society, initially known as "Mathsoc," was established at the Middlesex University Mauritius to give students a voice. Its mission was to empower students to take initiative and drive solutions in areas such as Mathematics, Statistics, and Numeracy support, extending their own progress beyond academic studies. Through initiatives like guest speaker series, workshops, training sessions, and employability applications, students were encouraged to lead their own development and advance the quantitative aspects of their programmes. This model was inspired by the University of Greenwich's Mathematics Society, founded in 2003 by one of the authors, Dr. B.K. Ashley Hoolash.

By 2014, the authors identified several challenges in adopting the University of Greenwich's Mathematics Society model at Middlesex University Mauritius:

1. The Mauritius campus, where the authors and Mathsoc (now CeMaSTeL) are based, did not offer specialist undergraduate or postgraduate Mathematics or Statistics programmes.
2. There were limited market opportunities to introduce these programmes in the future.
3. Non-specialist Mathematics and Statistics students showed little interest in leading Mathsoc's activities.

4. There was a lack of interdisciplinary collaboration among academics to support the society's growth.
5. As a relatively new campus (established in 2010 as a branch of Middlesex University, UK), Middlesex University Mauritius lacked the infrastructure to support extracurricular activities.

In response to the evolving challenges and leveraging prior experience in managing a support group for students needing assistance in Mathematics and Statistics, the authors undertook a comprehensive overhaul of this support structure in 2017. With the campus expanding both in size and in the demand for enhanced student services, it became imperative to improve the delivery of support. Initially, the authors transitioned the structure from a "society" to a formal Centre within the campus. Subsequently, the Mathsoc was rebranded as CeMaSTeL, marking it as the first Centre established at Middlesex University Mauritius. The authors resumed leadership of CeMaSTeL's activities, with newly defined objectives to extend support not only to non-specialist Mathematics students but also to academics and administrative staff requiring analytical assistance or confidence building. To broaden its impact, the authors strategically integrated the Centre into the Learning Enhancement Team (LET). With robust support from the campus management team, the authors developed and launched a fully operational website, accessible at <https://www.cemastel.org/>.

2. Alignment of CeMaSTeL to the Middlesex University Strategy 2031

The Middlesex University Strategy 2031 (Middlesex University, 2024) outlines four key principles that CeMaSTeL has strived to uphold.

Principle 1 puts students at the heart of the university's actions. CeMaSTeL exemplifies this commitment by being attuned to the diverse backgrounds and varied pathways of its students. It promotes interdisciplinary collaboration and innovation, nurturing creativity and curiosity among students. CeMaSTeL's scope extends beyond Mathematics and Statistics, encompassing a wide range of workshop themes such as Ethics, Literature Review, Research Design, and Methodology.

Principle 2 embodies a commitment to a creative, collaborative, responsible, and agile approach. CeMaSTeL demonstrates this by fostering collaborative activities across the UK and Mauritius campuses, with the potential inclusion of Dubai campus, thereby maximising the collective benefits of these global relationships. Over the years, CeMaSTeL has promoted interdisciplinary collaboration across departments, faculties, and campuses through shared resources and cooperative sessions. This platform offers a sustainable solution to the challenges it addresses, through its global reach showcased by "Workshops," "Events," and "Contributors" links on its website (CeMaSTeL, 2024).

Principle 3 embeds equality, diversity, and inclusion in all endeavours. CeMaSTeL embodies this principle by fostering a respectful, diverse, and supportive community where both staff and students feel a sense of belonging and value. Central to its mission, CeMaSTeL's activities are designed to ensure that all participants can achieve their full potential. Notably, CeMaSTeL has organised Research Retreats aimed at providing postgraduate students and researchers with a focused environment for academic writing. Further details on these initiatives are elaborated in Section 3.

Principle 4 promotes working in partnership with students to enhance students' experience and outcomes. At Middlesex University Mauritius, managing postgraduate deferrals has been a persistent challenge for both staff and students. CeMaSTeL effectively addresses this issue by offering targeted support during the dissertation write-up stage, ensuring that students receive the necessary guidance and resources to complete their work successfully. This collaborative approach not only mitigates deferrals but also fosters a supportive academic environment to help students to submit on time.

3. CeMaSTeL Workshops as a Strategic Tool to Empower Non-Specialist Mathematics Postgraduates

Drawing on their extensive teaching experience in the MSc Management programme since 2015 and the MA Education programme since 2013, the authors identified a critical need for student support in both qualitative and quantitative aspects of professional development. To address this, they designed a comprehensive schedule of targeted workshop sessions delivered in three modalities: online, in-person, and hybrid. This inclusive approach was tailored to accommodate the diverse learning needs of both full-time and part-time students. The flexibility in learning modalities significantly benefits postgraduate students, enhancing their academic and professional growth.

The authors observed that staff enrolled in various programmes, including the Postgraduate Certificate in Higher Education (PGCertHE), MA Higher Education, DProf (Doctorate in Professional Studies), and PhD, frequently sought extensive support from CeMaSTeL to enhance their analytical research skills.

CeMaSTeL has recorded and uploaded many specific presentations. In this paper, we detailed those which were delivered in 2024, targeting international postgraduate students, although the reach also encompasses any researcher interested in developing their research skills.

3.1. Speakers and Abstracts

1. Dr. B. K. Ashley Hoolash (Middlesex University Mauritius): *Analysis with SPSS*.
 - Abstract: A weekly, 2-hour long, in-person workshop, conducted between 20 January to 15 March 2024, to support researchers by introducing analytical techniques using SPSS to perform descriptive statistics, cross-tabulation, hypothesis testing, simple regression, and multiple regression.
 - This was attended by 21 students and 3 academic staff.
2. Sanjay Matadeen (Middlesex University Mauritius): *Middlesex University Institutional Research Ethics Application for Researchers*.
 - Abstract: A 1.5-hour long online session, conducted via Zoom on 17 July 2024, to inform and demonstrate the ethical approach taken when engaging in data collection with the potential for statistical analysis.
 - This was attended by 21 MSc Management students.
3. Mike O'Driscoll (Middlesex University UK): *Introducing NVIVO software to do Qualitative Analysis*.
 - Abstract: A 2-hour long online session, conducted by Zoom on 29 July 2024 introducing NVIVO software to empower researchers to analyse data collected from interviews and focus groups through a practical approach which complemented the theory of qualitative analysis, which they were more familiar with.
 - This was attended by 35 academic staff and 17 students.
 - Online link: <https://www.cemastel.org/workshops.html>
 - NVIVO – Two Workshops by Mike O'Driscoll (Workshop 2)

4. Dr. B. K. Ashley Hoolash (Middlesex University Mauritius): *Deconstructing the Research Onion*.
 - Abstract: A 3-hour long in-person workshop, conducted on 31 July 2024 including a workshop for two hours and scenario-based activities & discussions for one hour, to enhance students' comprehension of the different layers of research helping them in the structure of the thesis or research publications, particularly the research design.
 - This was attended by 21 students.
5. Anju Ajodah (Middlesex University Mauritius): *Interpretative Phenomenological Analysis (IPA)*.
 - Abstract: A 2-hour long online session, conducted by Zoom on 05 August 2024 giving a brief introduction to IPA which is a qualitative research approach focusing on subjective experiences of researchers and their subjects.
 - This was attended by 21 students.
6. Dr Sweta Rout-Hoolash (Middlesex University Mauritius): *Thematic Analysis*.
 - Abstract: A 3-hour long hybrid workshop, conducted on 22 August 2024 following Mike O'Driscoll's NVIVO session, introducing the steps involved in performing thematic analysis. A sample interview taken from Dr Ashley Hoolash's research was used to apply the workshop theory to practice.
 - This was attended by 21 students.
7. Dr. B. K. Ashley Hoolash (Middlesex University Mauritius): *Research Retreat and Networking event*.
 - Abstract: A weekly, whole-day, in-person retreat, conducted between 1 July to 15 September 2024 held every Tuesday to ensure a dedicated, silent time where researchers could focus on progressing their research write-up. A separate 1-hour long in-person networking event concluding the retreat allowed researchers to collaborate and discuss ideas.
 - The number of participants varied each week. On average around 10 students and 3 academic staff participated.

4. Transformational Intent and Impact

After careful critical reflection, the authors have identified several ways in which CeMaSTeL's workshops support advanced practice in the learning environment and has the potential to have broad ranging and transformational impact. The intention to foster global interdisciplinary intercampus cooperative relationships across the UK and Mauritius, potentially including Dubai in the future, demonstrates an innovative approach. It was the first 'centre' to be established at Middlesex University Mauritius. It offers targeted support to students and staff undertaking the research component of their degrees, responding to institutional challenges and delivering impactful solutions.

More concretely, participant feedback from the workshops further evidenced their impact. While all participants strongly agreed that the workshops were relevant, and supported their dissertation work, the reason they gave for this was the research support offered by the workshops. 100% of participants strongly agreed that the workshops made them feel more confident to write a more focused dissertation for their study programmes. Qualitative feedback received highlighted that workshops provided participants with clearer insights into a systematic approach to research

methodology including selection of methods, justification, sampling strategy, data collection methods and the interconnectedness of approaches, to positively impact quality of writing to demonstrate criticality in their dissertation. Improvement areas include introducing the workshop series earlier on in the academic year for more timely learning enhancements; and to add more workshops and more activities in the workshops.

The authors used the feedback received to build on their reflections and evaluations, improving the workshops design to have even more wide-ranging impact on the student experience in a sustainable manner across a range of needs for different audiences and individuals.

5. Acknowledgements

CeMaSTeL's vision of fostering collaboration with colleagues from other campuses and enhancing student learning experiences is gradually becoming a reality. We must recognise the invaluable contributions of colleagues in Mauritius and the UK, who have gone above and beyond to support the authors in their endeavours.

6. List of References

CeMaSTeL, 2024. *Centre for Mathematics & Statistics Teaching and Learning*. Middlesex University Mauritius. Available at: <https://www.cemastel.org/> [Accessed 01 March 2025].

Middlesex University, 2024. *Middlesex University Strategy 2031 Knowledge into Action*. Available at: <https://www.mdx.ac.uk/about-us/our-strategy-to-2031/> [Accessed 01 March 2025].

THIS PAGE
DELIBERATELY
LEFT BLANK

WORKSHOP REPORT

FYiMaths (First Year in Mathematics) New South Wales 2024 Meeting Report

Amanda J. Shaker, Department of Mathematical and Physical Sciences, La Trobe University, Melbourne, Australia. Email: a.shaker@latrobe.edu.au

Merryn Horrocks, Mathematics Education Support Hub, Western Sydney University, Sydney, Australia. Email: m.horrocks@westernsydney.edu.au

Deborah King, School of Mathematics and Statistics, University of Melbourne, Melbourne, Australia. Email: dmking@unimelb.edu.au

Don Shearman, School of Mathematics and Statistics, UNSW, Sydney, Australia. Email: d.shearman@unsw.edu.au

Abstract

This article provides a report of the recent First Year in Mathematics New South Wales (FYiMaths NSW) meeting held in Sydney, Australia, in December 2024. Nine talks were presented, with an overall theme of, *How should we teach and assess maths and stats to improve student outcomes?* An overview and background of FYiMaths is provided, followed by a summary of each of the nine talks presented at the recent FYiMaths meeting. Finally, a summary of the day is provided which includes emerging themes, key takeaways and lessons learned.

Keywords: FYiMaths, mathematics education, statistics education, student success, student outcomes.

1. Introduction

The First Year in Mathematics (FYiMaths, <https://fyimaths.weebly.com/>) network is a national collective of tertiary mathematics educators. Open and free to all, the network holds a two-day annual national conference. In addition, the FYiMaths New South Wales (NSW) group holds a one-day meeting each year.

For over a decade, FYiMaths has provided colleagues with opportunities to present their teaching and learning research, discuss successes and challenges, and share their experiences with colleagues from across the country.

The annual FYiMaths NSW meeting was held at Macquarie University as a hybrid event on 16 December, 2024, with the theme of, *How should we teach and assess maths and stats to improve student outcomes?* There were approximately 53 attendees in total, with 31 attending face-to-face and 22 attending online. Nine talks were presented throughout the day, each of which are summarised in Section 2, with recordings of the talks available at the FYiMaths YouTube channel at <https://www.youtube.com/playlist?list=PL-MI0q0vuCRU4BwRDIMrR3hlqg1wBvb6T>.

2. Talks

2.1. Conditional Reasoning in First-Year Mathematics Students (Lara Alcock: Plenary talk)

The day opened with a plenary talk by Lara Alcock from Loughborough University. Lara's talk explored the difference between mathematical, and everyday interpretation of conditional inference statements; that is, statements of the form "if A then B".

Throughout the talk, the audience was asked to engage in various tasks involving abstract inference statements, highlighting the difficulties in interpreting such statements, even for experienced practitioners.

The believability of true inferences was explored using comparative judgement (that is, where assessors are asked to compare solutions and decide which is better). Although truth and believability of the examples did not perfectly align, strong correlations were found between experts and students for those that did align.

The next result reported on included statements that were conditionals that had been classified as abstract, mathematical relatively believable or mathematical relatively unbelievable, and everyday causal relatively believable or everyday causal relatively unbelievable. Participants in the study were undergraduate mathematics students who had previously had some basic instruction in logic.

Results showed that students were better at accepting believability of mathematical inferences than everyday causal inferences and they accepted the truth of mathematical unbelievable inferences at about the same level as abstract inferences.

In general, students understood the difference between the truth of an inference and its converse, but were less reliable at identifying truth of "not A implies not B".

A small study on propositional inferences is underway, with earlier results showing that these are more challenging for students to comprehend.

2.2. Study on how maths and stats educators and students think that maths and stats should be taught and assessed - a progress update (Merryn Horrocks)

This talk reported on the progress of a study using structured interviews to capture educator and student perspectives on mathematics and statistics learning, teaching and assessment. 11 students (from Western Sydney University) and 33 educators (both Australian and International) had been interviewed to date, with more interviews planned. The study intends to apply a thematic analysis to the data.

Preliminary analyses found that students liked active learning activities, ongoing low-stakes assessments, and a variety of assessment types. There was great diversity in the educator views, but it was generally agreed that effective teaching and assessment modalities are dependent on the student cohort and the subject, and most were strongly in favour of active learning and peer-collaboration activities, and valued the development of mathematical/statistical communication skills in students. It is hoped that the formal data analysis will provide rich insights into methodologies and perspectives of educators actively involved in the teaching and learning of mathematics.

2.3. Smart Problem-Solving: From Strategies to AI Integration (Linda Banihashemi)

The speaker reported on a study design which has just received grant funding and which will be developed over the coming year. The project involves developing a module called Smart Problem Solving. Data show that many students have difficulty in using conventional problem-solving strategies. This, combined with low motivation levels, leads to overreliance on looking up the answers; in particular, students asking AI tools for solutions, rather than learning to develop their own solutions.

The project aims to develop an open access module that integrates conventional problem-solving strategies with AI tools to enhance numeracy and critical thinking skills. This will involve first teaching students problem-solving strategies and using them to solve specific problems, then exploring the use of AI to address the problems, and teaching students to critically evaluate the AI solutions, as well as how to validate their own solutions.

2.4. Improving pass rates in first-year statistics (Amanda Shaker)

This talk focussed on an intervention that was implemented within a large first-year statistics subject (module) with the aim of improving pass rates, with the impact on student anxiety and confidence also evaluated. The evidence-based intervention involved increasing the amount of early assessment within the subject, enabling students to progressively build their knowledge via low-stakes activities early in the teaching period, and assisting lecturers to identify at-risk students early in order to provide support.

Following the intervention, pass rates noticeably improved. General statistics anxiety did not significantly decrease as a result of the early assessment, however a significant decrease was seen in software-related anxiety. In terms of student perceptions, a significant and positive impact was observed, with students indicating that the early assessment had a positive impact on anxiety, confidence, learning, keeping up with the material, and motivation.

2.5. CARMA-MATRIX Maths Art Competition Awards 2024 (Judy-anne Osborn)

The speaker, CARMA Director, presented the 2024 award winners of the [CARMA/MATRIX Poster/Art Competition](#). Following an overview of the CARMA-MATRIX awards history, a presentation of the 2024 artwork entries was provided (e.g., Figure 1).

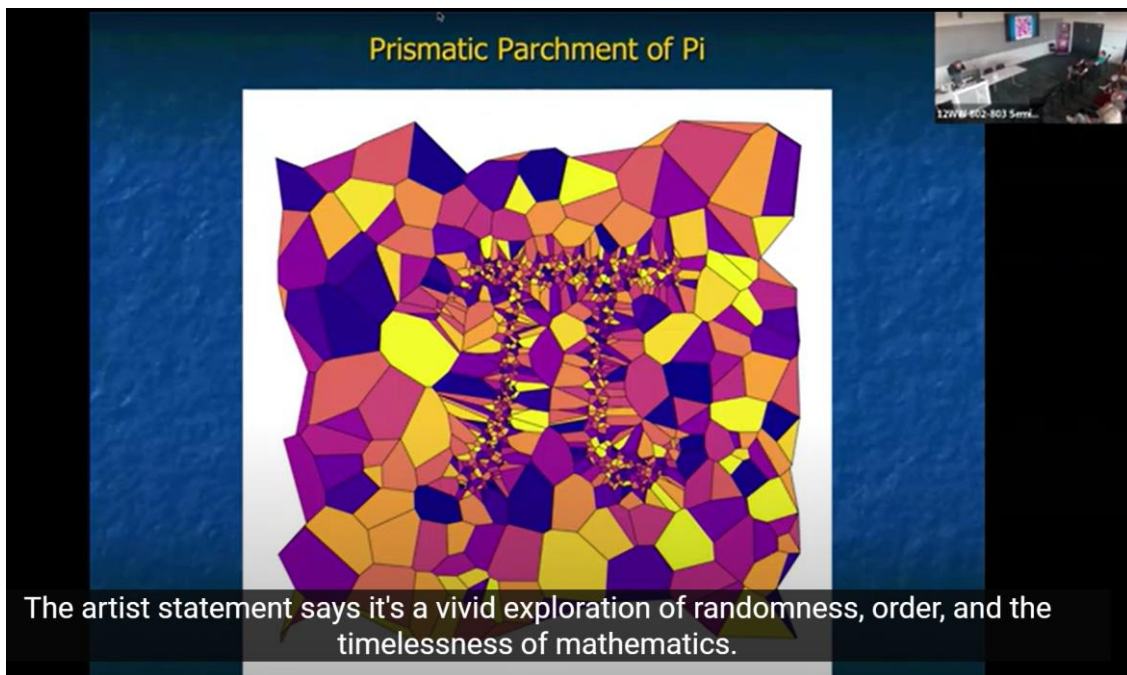


Figure 1. *Prismatic Parchment of Pi* by Jared Roberts.

The 2024 winners in both the Art and Outreach categories were announced as follows:

Art Prizes:

- 1st Prize: *Prismatic Parchment of Pi*, by Jared Roberts
- 2nd Prize: *Intergalactic moth*, by Awansika Nimuthumana and Anuradha Mahasinghe
- 3rd Prize: *Eratosthenes meets Ulam*, by Peter van der Kamp

Outreach Prizes:

- 1st Prize: *Wallpaper Groups*, by Ena Bahk-Pi
- 2nd Prize: *The Transition from Knots to Rational Numbers*, by Can Selek

2.6. Day-long mathematical modelling problems as outreach and assessment (Peter Bier)

This talk discussed a using a day-long project for senior secondary school students to promote and develop skills in mathematical modelling. Students worked in groups of 3-4 over 8 hours to solve an open-ended problem. Past problems have included “How many airships would be required to replace the Cook Strait Ferries?”, “If you had a million dollars, what percentage of the NZ population could you persuade to sign a petition you wanted championed?” and “What’s the largest payload that could be launched into orbit via slingshot?”. Students may use any public resources, including the Internet to help them develop their solution.

The aims of the day are to enthuse students and to get them to see the relevance of mathematics to real world problems. Much thought is put into choosing the questions, which need to be concise, open-ended with a low floor and a high ceiling, and currently unsolved. The questions are designed to encourage students to question their assumptions and to evaluate their solutions.

Around 1000 students from across New Zealand took part in the 2024 event. The speaker discussed some observations from the project, including the difficulty that students have in identifying the questions as maths problems (since they do not look like the maths problems they see in school), the stress they feel when the question does not provide all the data with which to solve the problem, and their euphoria when they finally submit their solution.

2.7. Discussion: Is student preparation declining? (Deborah King)

FYIMaths meetings endeavour to provide opportunities for the participants to discuss topics of general interest to the community. This provides valuable insights for colleagues on how their situation compares to other institutions and often leads to collaborative research initiatives across universities.

This session was intended to elicit perspectives on the current standard of student prior knowledge and if it has changed post-Covid.

Challenges noted by some participants included impacts of low attendance on student learning and lack of engagement with the material. Colleagues noted that students seemed to give low priority to university study and showed low levels of personal responsibility for their learning, but high dependence on staff to provide materials for them.

Some ideas that seem to be having a positive impact on students are live lecture streaming (rather than recorded lectures) and early assessment in subjects to provide feedback on progress.

The consensus view was that student prior knowledge continues to decrease but that this was not an evidence-based assessment.

2.8. Indigenising Statistical Learning through Project Work (Ayse Bilgin)

In this talk, the speaker discussed indigenisation of statistical learning through project work. In particular, [8 Aboriginal ways of learning](#) were presented, such as (4) Symbols and Images, and (7) Deconstruct/Reconstruct. The eight ways of learning were then mapped to essential elements of Work Integrated Learning in a statistical project context. For example, (4) Symbols and Images relates to the importance of data visualisation in statistics; (7) Deconstruct/Reconstruct relates to the importance of collaborating with clients when carrying out statistical consulting, especially where a roadblock has been hit. In this context, there may be additional information that the clients can provide, which can impact the data, story, and conclusions drawn. Utilising this framework, indigenisation of statistical learning was achieved, contributing to valuable career-ready skills development.

2.9. Effect of instant feedback on self-efficacy in a foundations mathematics course (Rosie Cameron)

The context of the research presented in this talk was a foundations mathematics course (module) at a New Zealand university. The student cohort was roughly 500 students and predominantly comprised of Engineering, Computer Science and Commerce students with diverse mathematical backgrounds. Pass rates were traditionally low and mathematics anxiety was present. In this course, students completed homework online in weekly quizzes using STACK (<https://stack-assessment.org/>). Upon answering a question, students could check their answer, receive feedback, and if desired, reattempt the question with a small penalty incorporated before moving on. Using focus groups, the effect of the instant feedback strategy was evaluated in terms of student self-efficacy and the results were presented.

Overall, the value of the quiz was made visible to students throughout the semester because they could see how the practice helped them to learn, and this was motivating for students. Some students also mentioned that the length of the quiz was challenging and found this to be de-motivating. Overall though, students found the quizzes to be motivating.

3. Concluding Remarks

The nine talks presented provided several key themes and takeaways related to the overall theme of *How should we teach and assess maths and stats to improve student outcomes?*

The most prominent emerging theme was provision of low-stakes assessments. In particular, the value of increasing the amount of low-stakes assessment early in the teaching period, and providing a mechanism for immediate feedback, was highlighted. These practices can lead to improved student outcomes, including student performance, student anxiety, confidence, and motivation, as well as student learning and keeping up with the material. Other benefits include the opportunity for students to progressively develop their knowledge and skills throughout a teaching period, and provision of a mechanism for lecturers to identify at-risk students early in a given teaching period in order to offer support.

Peer collaboration was another emerging theme, with evidence indicating that many educators value peer collaboration as an effective tool for student learning. The value of peer collaboration in conjunction with real-world problem solving was also discussed. Mathematical art was also presented as a real-world application of mathematics.

The importance of problem-solving skills was also discussed in the context of the emergence of Generative Artificial Intelligence (GenAI) technologies. In this context, it was suggested that while GenAI can and should be embraced as a learning tool, it is also important that students build their own problem-solving strategies, and learn to critically evaluate GenAI outputs.

Other topics covered included the use of active learning activities, and provision of a variety of assessment types, in order to improve student outcomes. The importance of understanding how students think and process logic was highlighted, and the value of indigenisation of statistical learning was demonstrated in terms of development of work-ready skills. Lecture streaming (rather than recorded lectures) was also raised as an important tool for student learning. The point was also made that which modes of teaching and assessment can largely depend on the student cohort and subject material.

Generally speaking, post-Covid challenges noticed by educators include low attendance, lack of student engagement with subject material, and increasingly complex student lives meaning that university study may be given lower priority. A general observation made was that prior mathematical background knowledge continues to decrease, although this observation was anecdotal rather than evidence-based.

The FYiMaths NSW meeting was a beneficial opportunity for mathematics and statistics educators to share experiences, discuss challenges, and share ideas with a view to improving outcomes for students. The next National FYiMaths meeting will be held mid-year in 2025, while the forthcoming FYiMaths NSW meeting will be held in December 2025. Details of future events will be published at the FYiMaths Events page (<https://fyimaths.weebly.com/events.html>).

References

Office for Teaching and Learning, 2015. First Year Coordinators in Mathematics. Available at: https://fyimaths.weebly.com/uploads/1/2/6/7/126775903/fyimaths_guide_web.pdf [Accessed 2 February 2024].

4. Acknowledgements

Thanks to Frank Valckenborgh, Carolyn Kennett and Chris Gordon from Macquarie University for their work in the organisation and hosting of this workshop.