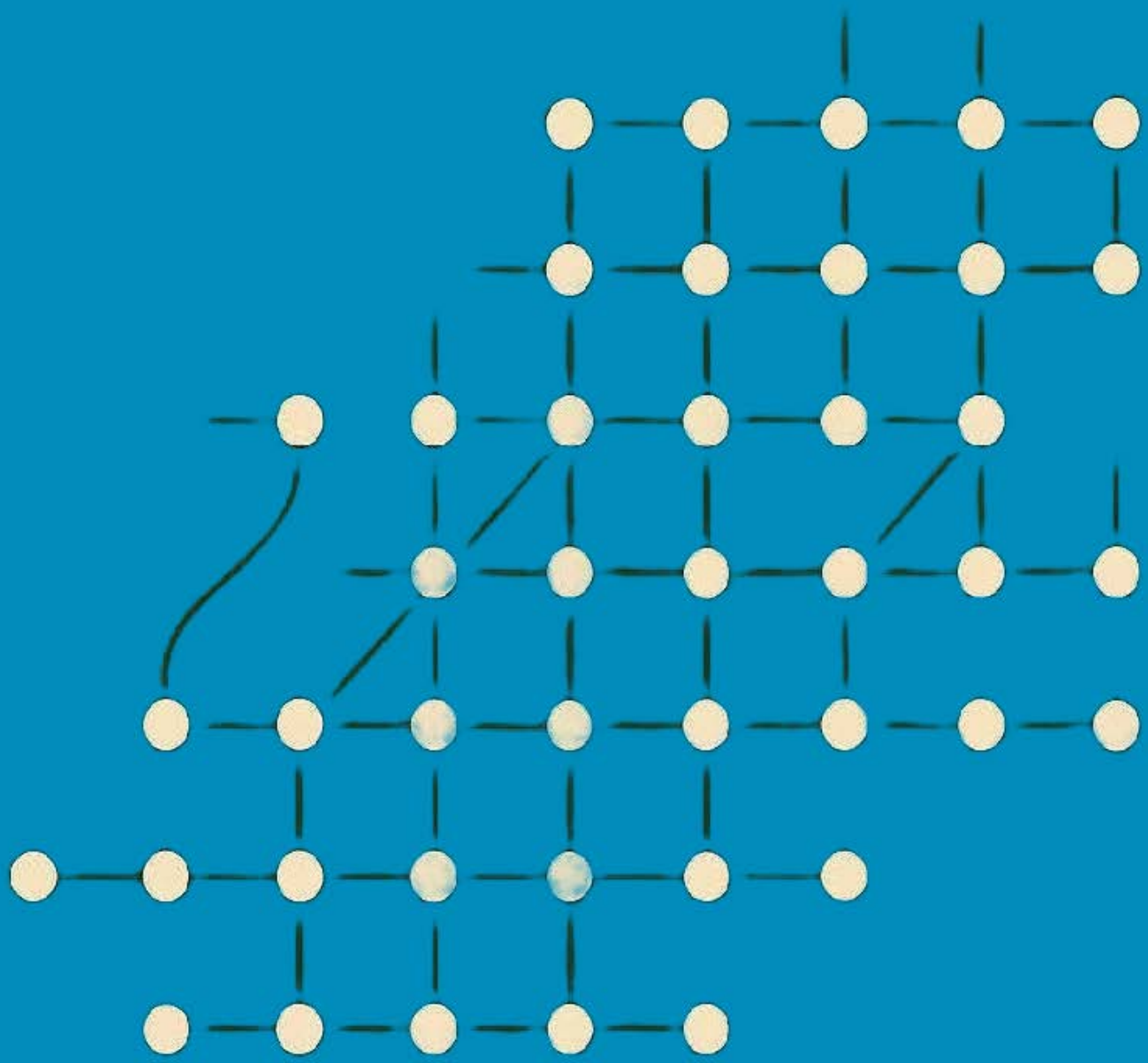
MSOR Connections

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 3. *Special Issue CETL-MSOR Conference 2025 Part 2*



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EDITORIAL

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Welcome to this issue of *MSOR connections*, the second of two issues featuring papers arising from presentations and workshops delivered at the CETL-MSOR Conference held at the University of Liverpool in September 2025. The conference brought together practitioners from the learning, teaching and support communities across Mathematics, Statistics and Operational Research, alongside those working in related disciplines such as Mathematics Education and Staff Development. The programme explored a wide range of topics including supporting students with statistics and data analysis, building student confidence with mathematics or statistics, transition of mathematics students into or out of higher education, initiatives to enhance student engagement or student community in mathematics and mathematics teaching and support in times of generative AI.

We apologise for the delay in publishing the work originally presented over a year ago, which was due to reasons beyond our control. However, we hope you enjoy reading these articles and that you find useful ideas that may guide and influence your practice.

The issue begins with three case studies which focus on ideas and initiatives to help improve access to and success on courses involving the study of mathematics. August and Coutts starts us off by reporting on a collaboration between Heriot-Watt University and University of Glasgow mathematics support services to develop a comprehensive diagnostic test based on Qualifications Scotland's (previously Scottish Qualifications Authority) Higher Mathematics, which is the essential foundation for most STEM degrees across Scottish Higher Education institutions. This is followed up by Forero Rincón et al. who describe work to improve the accessibility of a suite of online maths courses (developed pre-COVID) at SCQF levels 5, 6 and 7 (corresponding to the last 3 years of Scottish secondary school education). The final case study in this group is by Khalid that describes a two-year teaching initiative at Queen Mary University of London designed to improve mathematical confidence and competence among biochemistry, biology, zoology, and medical genetics students.

These are followed by four articles that explore approaches to skills development when studying mathematics or data science related subjects. The first of these is a case study by O'Sullivan that describes the embedding of algorithms and algorithmic thinking into a first-year undergraduate pure mathematics course at the London School of Economics (LSE). The next article by Buckingham (also a case study) then explores the use of annotation sheets, containing the algebraic steps of proofs or derivations with spaces left for students to add explanations, as a means of providing structured note taking which allows students to focus on the reasons behind the steps. The third by Solanki (also a case study) presents a novel learning activity, called Deeper Discussions, for developing such skills within mathematics education. This group of articles is then rounded off by a research article by Mott that explores the use of authentic assessment through real-world tasks to support the development of soft skills demanded by employers.

The issue is then completed by two articles that focus on statistics education. The first of these is a case study by Kuveke et al. which describes updates to the design, delivery and performance of a first-year undergraduate statistics subject (or course/unit/module), entitled Making Sense of Data, at La Trobe University, Australia. This is then followed by a workshop report from Riach et al. who

describe Workshops held in 2025 aimed to provide a dedicated space for experts to talk and, importantly, document their professional experiences and perspectives so that these ideas could be disseminated to the wider community of Higher Education statistics educators internationally.

We would like to say thank you to all these authors for sharing their work. *MSOR Connections* can only function if the community it serves continues to provide content, so we strongly encourage you to consider writing 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. However, just as important are the many reviewers who continue to contribute hugely to the sharing of this good practice and experience, but often go unacknowledged – thank you too for all your support for the journal. We can all help with the functioning of the journal by volunteering as a peer reviewer. When you register with the journal website, there is an option to tick to register as a reviewer. It is very helpful if you write something in the 'reviewing interests' box, so that when we are selecting reviewers for a paper, we can match you with articles we feel you would be comfortable reviewing. To submit an article or register as a reviewer, just go to https://journals.gre.ac.uk/index.php/msor and look for *MSOR Connections*.

CASE STUDY

Bridging the Gap: A Collaborative Approach to Mathematics Diagnostic Testing for STEM Student Transition in Scotland

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Abstract

This case study reports on a collaboration between Heriot-Watt University and University of Glasgow mathematics support services to develop a comprehensive diagnostic test based on Scottish Qualifications Authority[1] (SQA) Higher Mathematics, which is the essential foundation for most STEM degrees across Scottish Higher Education institutions.

Building upon the work of Shearman et al. (presented at CETL-MSOR 2023), our test was developed using NUMBAS's diagnostic mode, carefully mapped to SQA Higher Mathematics learning outcomes. This provides students with immediate feedback on their mathematical preparedness, whilst also generating detailed analytical data for mathematics support practitioners and academic staff. This paper details the development phases, including the initial pilot deployment and subsequent refinements based on user feedback and performance data. We further discuss our future plans to make the test openly available to students, lecturers, teachers and pupils across Scotland.

Keywords: Diagnostic testing, Transitions, Scotland.

1. Introduction

Diagnostic tests in mathematics are used widely in universities as a way of assessing student readiness for their chosen programme and informing both staff and individuals of potential gaps or weaknesses in pre-university knowledge. Some of these diagnostic tests have been administered to incoming students over many years and provide a comparison of incoming student competencies from cohort to cohort. Coventry University introduced their test in 1991 (Hodds 2021), while in the Scottish context, the University of Edinburgh (Akveld and Kinnear 2024) has administered a test in a digital format since 2011 (Maple TA from 2011-2017 and STACK (Sangwin 2025) since 2017). These are only two examples of long running diagnostic tests, but the use is widespread in the UK, Ireland and beyond (Hyland and O'Shea, 2022, Rylands and Shearman, 2022, Reddy et al. 2025, Cronin, Shearman and Reddy 2023). In Ireland, a study by Hyland and O'Shea (2022) showed that 70% of institutions used diagnostic testing, while Lawson (2003) showed that 60% of departments in the Learning Teaching Support Networks for Engineering, Maths Stats & OR, Physical Sciences and The UK Centre for Materials Education were delivering mathematics diagnostic tests. Gillard, Levi and Wilson (2010) conducted an email survey of maths departments across the UK where 60% of responding institutions reported that they delivered a diagnostic test for incoming students.

[1] The Scottish Qualifications Authority (SQA) changed its name to Qualifications Scotland after this paper was submitted for publication. All references to the SQA now relate to Qualifications Scotland.

Rylands & Shearman (2022) discuss the use and purpose of diagnostic testing in two case studies at Western Sydney University, while Cronin, Shearman & Reddy (2023) provide an overview and comparison of diagnostic testing in Ireland, Australia and the USA, highlighting the differences in implementation, as well as the shared purposes of student support and success.

In all the studies, the delivery of the diagnostic test varies from institute to institute and over time. Pen and paper tests were the preferred method in the responding institutions to the Gillard, Levi and Wilson (2010) survey while it seems that more recent testing is predominantly online. Though there is not a more recent survey to collate this, a few examples of online diagnostic tests are reported at ETH Zurich and the University of Edinburgh (Akveld and Kinnear, 2024), Western Sydney University (Shearman, Aziz and Pettigrew, 2024), and at Coventry University which switched to online in 2020 as a response to the Covid-19 pandemic (Hodds, 2021).

In Scotland, students pursuing a degree in STEM subjects are expected to have a good grasp of the mathematical concepts covered in Scottish Qualifications Authority (SQA) Higher Mathematics (Scottish Qualifications Authority, 2023). This is the standard mathematics qualification taken in either the penultimate or final year of school in Scotland and is an entry requirement for most[2] STEM degrees in Scotland. Without this background, students may struggle on their degree programme where new material will build upon this implied foundation.

However, it is widely recognised that not all students have the same educational background, with curriculums varying from country to country, and even from school to school. The increase of widening participation/access initiatives at institutions across the country (see O'Toole et al., 2024 for an overview of widening access) has led to, a very welcome, diversification of the student body, but this also increases the variability of pre-university knowledge. Due to the 4-year degree structure of a standard BSc degree in Scotland, the first year is often used as a time to 'level' the students' incoming knowledge. In this context, we realised that we had similar motivations for developing a diagnostic test and those can be summarised in two main aims:

1. Allow (any) teaching staff to identify the common weaknesses of their cohort of students.
2. Allow students to identify gaps in their knowledge/skills.

Crucially, in the context of both of these aims, there must be follow up interventions, advice and support to allow the growth and development of students' mathematical skills and confidence. While this is recognised (and briefly discussed) in this case study, the focus of the paper is on the development and deployment of the test.

Our test is deployed in NUMBAS (Lawson-Perfect et al. 2025), which is a freely available, open-source, online assessment system developed at Newcastle University that has an inbuilt adaptive algorithm, and we will discuss the methodology and process of developing the test in a step-by-step manner. In discussing the implementation, as well as the choices and development of questions, we aim to provide a practical guide for others who wish to develop a diagnostic test in this way. The test was first deployed to students in the 2024/25 academic year after which refinements were made, before being delivered to a larger number of students in academic year 2025/26.

[2] There are a few exceptions to this requirement, and it must be noted that there are some non-STEM subjects, such as economics, which also have this requirement.

2. Methodology

2.1 DIAGNOSYS Algorithm

As discussed above, our goal was to develop a tool that would help students identify their strengths and weaknesses within the SQA Higher Mathematics curriculum. However, it was also key for us that the test should not take too long for students to complete; this was partly to avoid intimidating students who are new to university with a long test, and also to improve completion rates by avoiding a situation where students give up halfway through. Ideally, the test should take less than 60 minutes so that it fits within a standard class.

Following the work of Shearman, Aziz and Pettigrew (2024), our approach was to create a test using the inbuilt *Diagnostic* mode within NUMBAS (Lawson-Perfect et al 2025). This uses an algorithm called DIAGNOSYS to create an adaptive test which is based on an underlying hierarchy of skills/topics, known as the *Knowledge Map*. The general idea is that students start somewhere in the middle of the hierarchy, and their next topic is determined by whether they get that question correct or incorrect:

- If they get the question correct, we assume that they would have also correctly answered any question on a prerequisite topic, and thus we mark those questions as correct without the student seeing them;
- If they get a question wrong, we assume that they would also have incorrectly answered any subsequent question building on that topic, and thus we mark those questions as wrong without the student seeing them.

For example, consider a toy version of the Knowledge Map shown in Figure 1. Suppose a student was initially presented with a question on Topic B. If they get that question correct, then the question for the prerequisite Topic A is also marked as correct and they would move on to trying the harder Topic C or D. If they get the initial question wrong (B), then the questions on Topics C and D would also be marked as incorrect and they would be given a chance to try the easier Topic A question.

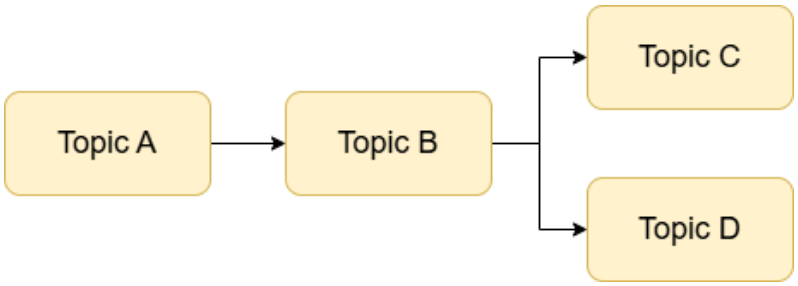


Figure 1. An example Knowledge Map showing four topics with the dependencies marked using arrows. It illustrates that Topic A is a prerequisite for Topic B, and Topic B is a prerequisite for Topics C and D.

Students continue to answer unmarked questions until there are none left and, in this way, the students are marked on a broad range of topics without having to see them all, helping to limit the amount of time required to take the test. We also hope that it avoids lower ability students becoming overwhelmed by seeing increasingly difficult questions. The first step of the test development is therefore to decide what skills need to be tested, and how to arrange them into the Knowledge Map.

2.2 Knowledge Map

Formally speaking, the Knowledge Map consists of a directed acyclic graph, where each vertex is a skill/topic that we wish to assess, and an arrow is added from vertex A to vertex B if Topic A is a prerequisite for Topic B. Crucial to the success of this approach is to create a Knowledge Map that accurately reflects the dependencies between different topics.

We began by determining the overarching *Learning Outcomes* that we wanted students to get feedback on. These are the categories that individual skills or topics[3] belong to, and at the end of the test, students are told whether or not they have mastered each Learning Outcome based on the percentage of questions within that category that get marked correctly. Our Learning Outcomes were decided by studying the SQA Higher Mathematics curriculum, along with looking at chapter titles in common textbooks for the course, so that test users would be able to easily find resources to act on their results, even if they do not have access to maths support. The Learning Outcomes chosen were:

- Numeracy - Fractions and Percentages (included in 2024, but removed for 2025)
- Algebra
- Polynomials
- Functions
- Powers and Logarithms
- Trigonometry - Angles and Graphs
- Trigonometry - Identities
- Straight Lines
- Vectors
- Differentiation (added in 2025)
- Integration (added in 2025)

Note that Differentiation and Integration were only left out of the first implementation due to time constraints, while Numeracy was removed to stop the test from becoming too long once these additional topics were added (and it is implicitly tested within the other Learning Outcomes).

Once we had the overall Learning Outcomes, we then used the details of the SQA Higher Mathematics curriculum (Scottish Qualifications Authority, 2023), along with our experience of what students often struggle with during their university studies, to determine the individual topics. Moreover, to help build the hierarchical structure, the skills listed in the curriculum were complemented with some prerequisite skills that are covered in the previous mathematics course, SQA National 5 Mathematics (roughly equivalent to GCSE Mathematics). For example, factorising a quadratic is already covered in the National 5 curriculum, but adding such skills to the test allows students with lower capabilities the opportunity to successfully answer questions at a lower level, hopefully avoiding demotivation. Once we had a full list of skills, each of these skills was created as

[3] A note of terminology: In NUMBAS, 'Learning Outcome' is the term used for the overarching area of mathematics while 'Topic' is used for a sub-area (i.e. the individual vertices of the Knowledge Map). In the SQA course specification document 'Skill' is used for both overarching areas of mathematics and their sub-areas.

a Topic in NUMBAS (see the NUMBAS Implementation section below for details) and each Topic was assigned to one of the Learning Outcomes listed above.

The next stage was then to add the dependencies, which we did by using our own experience. This was not always easy, and it sometimes depended on the particular question that would be chosen to assess the topic. For example, the prerequisites for an optimisation problem can depend on the type of function you are required to optimise, e.g. it would not be accurate to assume that because someone can optimise a polynomial expression that they can also differentiate trigonometric expressions. For this reason, there were several iterations of the Knowledge Map as we continued to come back and make edits once in the question selection stage.

A copy of the Knowledge Map created for our 2024 test is included in the appendix. This was edited for our 2025 version (see the Evolution section below), and we anticipate even further refinement once we start to analyse the 2025 results.

2.3 Question creation/selection

For each topic (i.e. vertex of the Knowledge Map), we needed to select at least one question that tests that particular skill. As discussed above, care was taken to ensure that the questions chosen reflected the choices made regarding dependencies when creating the Knowledge Map. NUMBAS supports the creation of different types of questions which allows for a more varied assessment, e.g. multiple-choice questions, mathematical expressions, number entry, matrices and interactive graphs/diagrams.

It is possible to provide more than one question per topic, but a given student will only see at most one of these - if they reach that topic, the algorithm will randomly select one of the questions. For example, using SOHCAHTOA to answer questions about right-angled triangles was kept as a single topic, but we added three questions so the students would randomly be assigned sin, cos or tan. It is useful to note that students do see the title of each question during the test, so we were careful to avoid giving away in the title which function they should choose.

Some of our questions were written specifically for this test, but many came from or were adapted from a bank of NUMBAS questions created by SCHOLAR (SCHOLAR 2025) – a digital learning initiative by Heriot-Watt University that provides resources for teachers and pupils in Scottish schools. Since we had approximately 90 topics to assess (and hence create questions for), this was a significant time-saver.

When choosing and writing questions, we aimed for them to have a randomised component so that students could repeat the test if they desired, without getting exactly the same questions. This even applied to graph-based questions where GeoGebra applets (GeoGebra, 2025) (which NUMBAS supports) were used to provide randomised graphs, e.g. plotting functions with randomised coefficients or parameters.

2.4 NUMBAS implementation

Once the Knowledge Map has been created and the questions have been written in NUMBAS, the implementation of the diagnostic test is straightforward. At the time of writing, the first step is to create a standard NUMBAS exam, and then from the Navigation pane, change the ‘Question navigation mode’ from ‘Sequential’ to ‘Diagnostic’.

At this point, we also chose to deselect the boxes that allow students to enable steps, reveal answers or regenerate questions since the purpose of the test is to establish their current strengths and

weaknesses. However, to avoid students' results being significantly impacted by a typographical, syntactical or basic calculation error, the algorithm automatically allocates them three retries to use during the test. If they get a question wrong, they can choose to use one of the retries to have another go at that same topic.

Once Diagnostic mode is selected, a Diagnostic pane will appear which has tabs for:

- Learning Objectives - these are the question categories that topics fall into, and are what students will get feedback on at the end of the quiz (e.g. 76% for Vectors);
- Topics - these are individual skills that you want to ask questions about (i.e. the vertices of your Knowledge Map);
- Diagnostic algorithm - here you can find (and customise) the DIAGNOSYS algorithm that will implement the marking described at the beginning of this section, so that students only see a selection of the questions.

Once you have added your Learning Objectives and Topics, you can then fill in the dependencies from your Knowledge Map using the Topics tab. For each topic, add other topics in the 'Depends on' box (those at the start of arrows ending at that vertex), and in the 'Leads to' box (those at the end of arrows starting at that vertex). An example is shown in Figure 2.

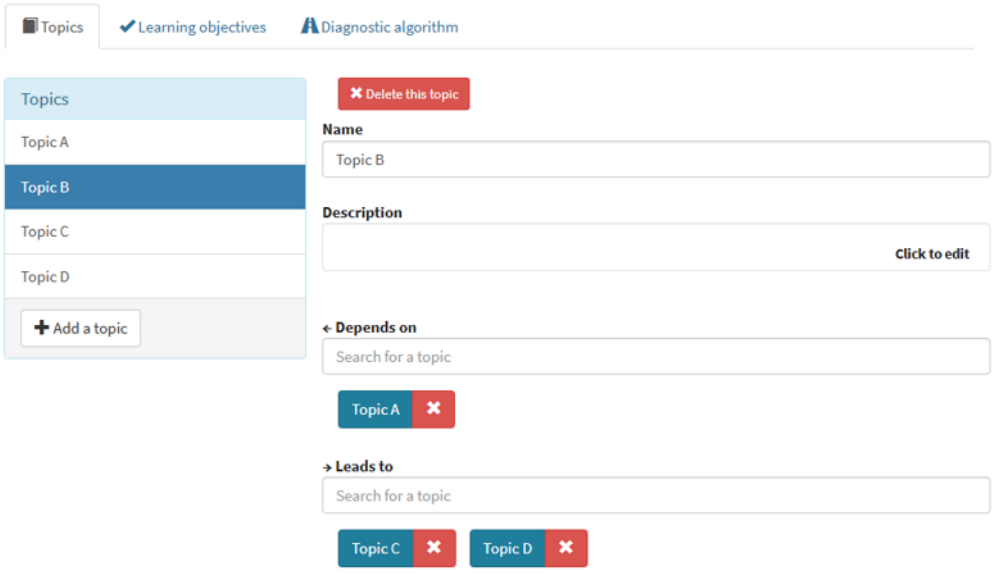
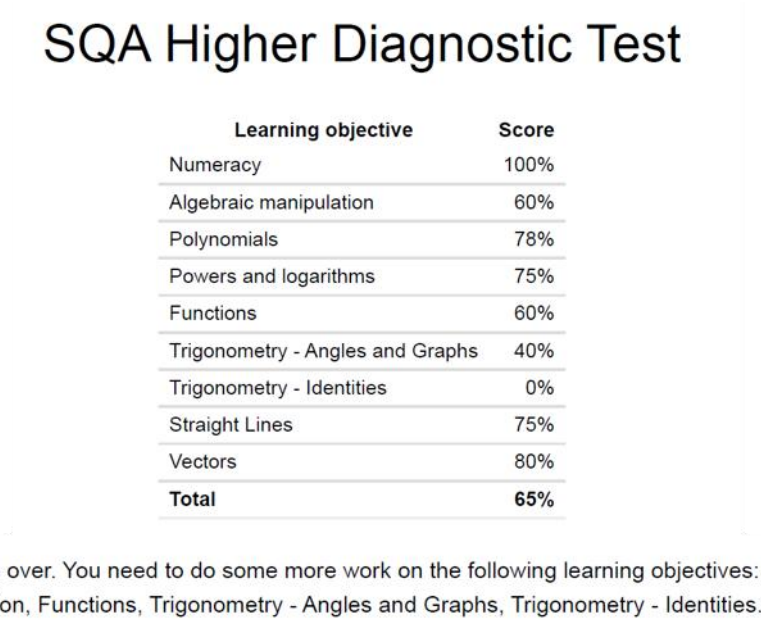


Figure 2. A screenshot from NUMBAS showing that, based on the Knowledge Map in Figure 1, Topic B would have Topic A in the 'Depends on' box, and Topics C and D in the 'Leads to' box. Similarly, Topic C would have Topic B in the 'Depends on' box, and nothing in the 'Leads to' box.

The final stage is then to go to the Questions pane (where the list of topics will appear) and add your chosen question(s) to each topic. This creates a working diagnostic test, although there are further things you can choose to customise in the Feedback and Navigation panes. For example, if a student skips a question, it is automatically marked as incorrect, and so, to avoid any confusion, we changed the 'action on leaving a question' to 'Prevent if unattempted' to ensure the student must enter something to proceed. We chose not to set a time limit as students may then receive feedback that they need to improve on a Learning Objective they did not have time to attempt. Additionally, we changed a setting in the DIAGNOSYS algorithm (on the Diagnostic pane) so that students start on

a random question, rather than the default of always on the middle question. Again, this makes repetition of the test more useful, as it is less likely they will follow the same path of questions if they start in different places.

At the end of the test, students receive instant feedback on their results, as shown in Figure 3.



SQA Higher Diagnostic Test

Learning objective	Score
Numeracy	100%
Algebraic manipulation	60%
Polynomials	78%
Powers and logarithms	75%
Functions	60%
Trigonometry - Angles and Graphs	40%
Trigonometry - Identities	0%
Straight Lines	75%
Vectors	80%
Total	**65%**

The test is over. You need to do some more work on the following learning objectives: Algebraic manipulation, Functions, Trigonometry - Angles and Graphs, Trigonometry - Identities.

Figure 3. A screenshot showing an example of the feedback students receive immediately on completing the test.

For delivery to our students, we chose to augment this feedback (by customising the algorithm within the Diagnostic pane) with extra information and links to the relevant maths support services at our institutions, as the follow-up to a diagnostic test is vitally important if it is to make an impact to student learning. Note that the threshold for the message “You need to do some more work on the following learning objective…” is customisable and can be set at a level of your choosing using the Feedback pane.

2.5 Delivery

2.5.1 Integration with Virtual Learning Environments

After the test has been developed within NUMBAS, there are a variety of ways in which it can be delivered to students, giving flexibility to the practitioner. The method chosen will depend on several factors – predominantly the Virtual Leaning Environment (VLE) used at the institution.

At the University of Glasgow, the test was made available to all students as an optional tool on the maths support Moodle (VLE) page. Delivery via Moodle was achieved by downloading the SCORM package from NUMBAS and uploading it as a Moodle activity which was easy to do.

At Heriot-Watt University, Canvas is the VLE used and at the time of the first deployment (September 2024), delivery of the test using the SCORM package did not work as expected and it did not integrate with the gradebook in the VLE. To address this challenge, the test was delivered in standalone mode, where the test runs in a web-browser and students downloaded their attempt data

at the end and sent it to us. This approach allowed some results to be gathered for test refinement but created issues: students did not always download and submit their attempt data, or they sent screenshots of instant feedback instead of the correct data files. It must be noted that the time of first deployment the 'Analyse attempt data' tool within NUMBAS (which decrypts and displays the attempt data) could not handle exams in diagnostic mode: the NUMBAS team helped to find a workaround and allow us to access the attempt data.

After following internal software approval processes, the NUMBAS LTI (LTI is Learning Tools Interoperability, which allows tools like NUMBAS to be used in different virtual learning environments and interact with areas of the VLE such as the Gradebook) was implemented by the Heriot-Watt Information Technology Team which addresses the issues found with the SCORM package and successfully integrated the test with the VLE. Within the VLE, the NUMBAS LTI provides summaries of the attempt data for the cohort, as well as individuals.

The summaries provided by the NUMBAS LTI (and equivalent csv file) do not give full attempt data such as the path taken through the test or the time spent on individual questions. Therefore, in order to interrogate the attempt data further (from both institutions) and find more detailed information, Python code was written to extract relevant information from the json file that can be download for each test attempt.

2.5.2 2024 Student Cohorts

Students with SQA Higher Mathematics as a prerequisite for their course at University of Glasgow were encouraged to take the test in order to get advice on which of the Maths Refresher sessions they would benefit from attending. While at Heriot-Watt University, in 2024, the test was made available to any student at the university, but it was made compulsory for first-year students taking their initial calculus course. This course was selected following a request from the lecturer, who sought a way to assess students' levels, identify weaknesses, and highlight gaps in prior knowledge. This HWU cohort led to around 100 test-takers, but only 21 complete result sets were obtained and used to inform refinements to the test alongside our own evaluation.

2.5.3 2025 Student Cohorts

By the start of the 2025/26 academic year, the technical obstacles had been resolved, enabling seamless delivery within the VLE without requiring students to submit attempt data manually. The test remained compulsory for first-year calculus students at Heriot-Watt University and was extended to foundation students on science programmes, resulting in 328 students of varying background levels of mathematics taking the test at HWU (note that all had SQA Higher maths as a prerequisite). As in 2024/25, the test was not delivered to any specific cohort at the University of Glasgow, but was available as an optional tool for students with SQA Higher maths as a prerequisite for their university course,

2.5.4 Communication

In both iterations of the test so far, a lot of care was taken over how the details of the test were communicated to the students in order to minimise any distress/anxiety associated with taking a test in the first few weeks of their university journey. A guide was produced to explain the reasons for diagnostic testing as well as practical information on using the NUMBAS platform and signposting students to the support available from maths support and their lecturers. To reinforce the message, maths support practitioners delivered in-person information sessions to the cohorts for whom the test was compulsory. At HWU, the first-year calculus class were permitted to take the test in their own time, while the foundation science students had to take the test in-class. This decision was at

the discretion of the course lecturer and, of course, leads to questions of academic integrity in the case where students took the test at home. However, the students only receive a very small percentage of their final grade from taking the test (or not), not the mark they received in the test. The aim was not to give them a grade, but to give the student and the lecturer information about the prior level of knowledge in order to support their learning.

The information sessions also explained that the diagnostic testing was being run alongside a research project, and while participants had to take the diagnostic test, they could opt in or out of the research survey. See the future work section for more information on this.

3. Results

From the 2024/25 deployment of the test, only a small amount of data was gathered; namely 21 complete attempt data files. From the 90 questions that are within the test, the average number of questions actually seen by the students was 51.14 due to the adaptive algorithm. Figure 4 shows a summary of the results (direct, raw scoring only) in the form of a heat map, where the colour corresponds to the score, each row relates to different respondents and each column to a different question. The low data return meant that the results did not give a complete picture of the cohort, but it was used to help us refine the test for the 2025 version.

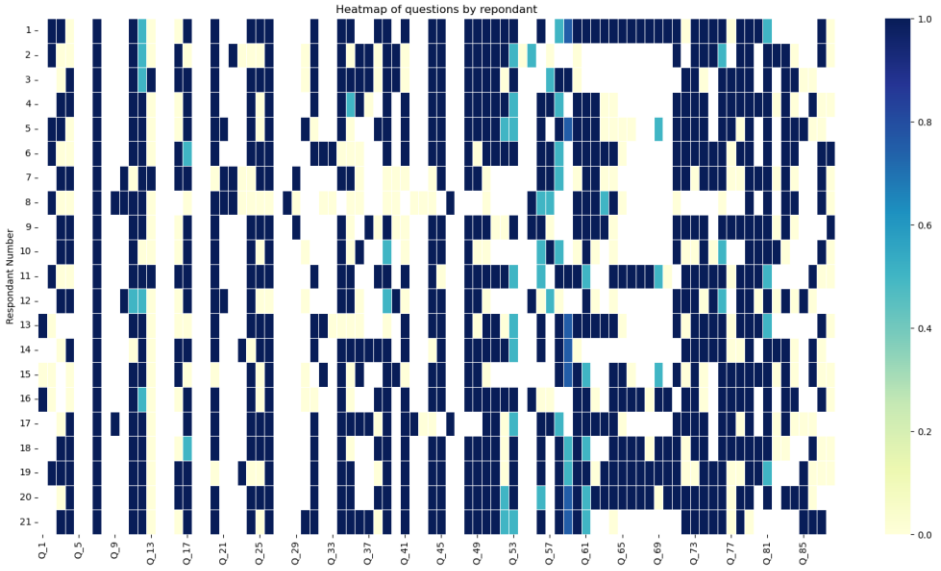


Figure 4. This heat map shows the raw score received by each respondant for each of the questions attempted.

At the time of the presentation at CETL-MSOR 2025, the second deployment was only just beginning but by the end of the first semester, 328 students had completed the test and a basic summary of results were produced (on a cohort level) for the lecturers involved. In this iteration, of the 89 questions within the test a student would see on average 43.57 questions during their attempt due to the adaptive algorithm. This reduction in the average number of questions seen by a student cannot be directly attributed to the change in the test from 2024/25 to 2025/26, as there is simply not enough data; it is merely a measure of the length of the test.

4. Discussion

4.1 Evolution

For the initial deployment, which needed to be ready for September 2024, we ran out of time and space to include the calculus topics. Even without these included, there were 90 topics in the test, and our trial runs were taking longer than our goal of 60 minutes. We therefore edited our Knowledge Map and questions before redeploying our test in 2025, which involved removing and/or merging some topics and adding in the calculus topics. Some of the principles we used to decide which topics to cut were as follows:

- We prioritised topics that were regularly used in university studies, based on our knowledge of the courses at our universities and the questions we are commonly asked by students, e.g. we removed the questions on calculating medians from the 'Straight Lines' Learning Objective, and the question from 'Trigonometry: Identities' asking students to express the wave equation as a single sin or cos expression;
- The Learning Outcome `Numeracy' was cut as the topics it contained were all prerequisites for Higher Mathematics, rather than part of the curriculum itself;
- Questions which were intended to be non-calculator (such as the question using exact angles in the `Trigonometry: Angles and Graphs' Learning Outcome) were removed as there is no way of guaranteeing students do not use a calculator;
- Time consuming questions were cut (this data was available from the json files), edited or merged to increase the efficiency of the test, e.g. the questions asking students to use the double angle formulae for sin and cos were merged into a single topic and the questions identifying various parameters from a trig graph (amplitude, phase, shifts) were adapted so they did not contain so many individual parts;
- We analysed the attempt data from the 2024 deployment and reviewed any questions which scored either very well or very poorly. We also looked at which questions no student had seen due to the algorithm marking them correctly or incorrectly based on other questions. This resulted, for example, in the three questions on varying levels of multiplying out brackets being merged into one, as two of them had not been seen by any of the students. We did, however, choose to keep some of the easier questions that had not been seen by any students, as most students would not see them (and hence they would not contribute to the length of the quiz), but they provided some achievable questions for struggling students.

After removing questions and adding in the two Learning Outcomes 'Differentiation' and 'Integration', our 2025 version of the test contained 89 questions. We anticipate that we will continue to make edits for the coming year.

4.2 Future Work

For the 2025 deployment of the test, we developed a short survey (full ethics approval has been granted for this research) to gather basic pre-university information from the students including:

- Did they take SQA Higher Mathematics?
- What was their last maths qualification?
- What grade did they receive?
- Likert scale questions assessing their confidence with the learning outcomes.

We are also planning to send out a follow up survey asking students how the test made them feel (both when being told they need to take it, and after they had taken it) and repeating the Likert scale

questions assessing their confidence with the learning outcomes. Using this data alongside the results of the test and students' first year grades, we hope to:

- Obtain a more complete picture of students' transitions to university, including common areas of weakness and/or lack of confidence;
- Further analyse the results of the test to assess whether it is a reliable indicator of success in first-year mathematics courses at university and refine the Knowledge Map and/or questions using techniques such as items analysis;
- Establish the effect of the test on students' confidence in mathematics;
- Investigate whether students experienced anxiety surrounding the test.

Our hope is to make a public version of the test that can be used widely in schools, colleges and universities across Scotland. One of the advantages of using NUMBAS for the test development is that there are multiple ways the test can be deployed to students so educators can integrate it to their systems and adapt feedback messages to their individual settings. The test has already been shared with the maths support service at the University of Aberdeen. By making this resource freely available to the wider academic community, we aim to support mathematics educators and student support services across the sector in addressing the persistent challenge of knowledge gaps that affect even high-achieving students during their transition to university-level mathematics

5. Appendix

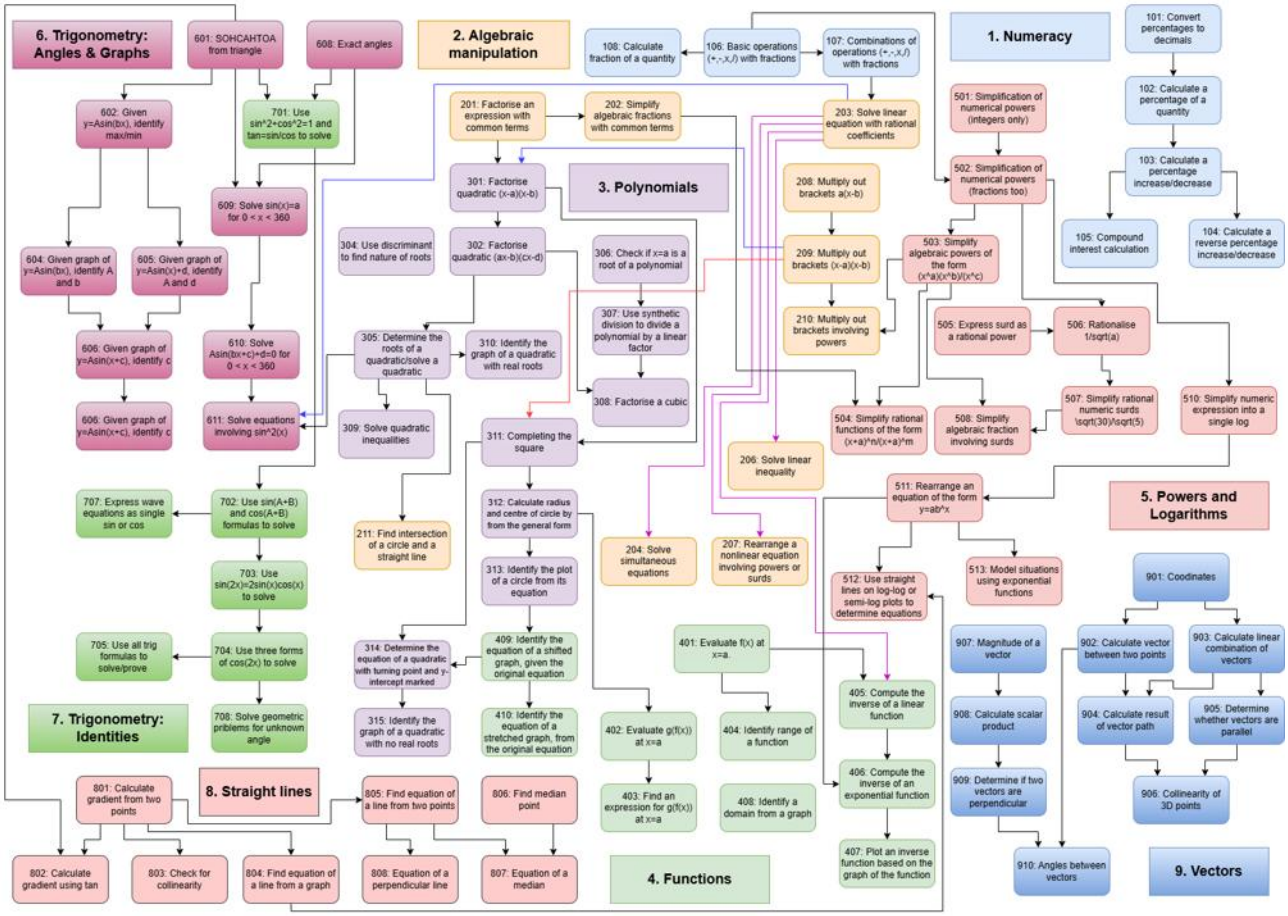


Figure 5. A copy of the Knowledge Map used for our 2024 version of the diagnostic test. Coloured arrows are designed to help the reader follow long arrows and have no other significance.

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CASE STUDY

Towards Making an Online Access Maths Course Accessible to All

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Abstract

The authors' institution developed pre-COVID a suite of three access online maths courses, at SCQF levels 5, 6 and 7 (corresponding to the last 3 years of Scottish secondary school education). These courses were designed to be 'do-it-yourselves' and are entirely online. They have grown in popularity and have attracted a wide range of applicants from around the country, and beyond, as a way into higher education. The material was written before the maths education and support community started systematically investigating the issues of making mathematics digitally accessible, and therefore, did not implement any of the good practice that experts now promote. Guidance has been produced since, however, and as the institution received two expressions of interest from prospective students with visual impairment in the past two years, it was time to make the access courses accessible. This involved work with Word and LaTeX material, diagrams, figures, as well as hand-written material. It also required thinking carefully about approaches to teaching concepts of foundation mathematics to be understandable by a visual-impaired audience. In this paper, we describe the changes we implemented and formulate advice for the design of accessible foundation maths.

Keywords: digital accessibility, online education, mathematical sciences, inclusion and diversity, access to education.

1. Introduction

1.1 The Maths Access Programme

The School of Education at the University of Aberdeen were aware of adults interested in applying for a teaching career or a change of career but who lacked the necessary minimum mathematics qualifications. As individuals could be in employment, an online course was developed to allow for flexibility of study. In 2018/2019 a team developed the first Mathematics Online Access course, at Scottish qualification level SCQF 5 (equivalent to English level RQF 2) (Scottish Credit and Qualification Framework, 2026). Once enrolled, students have access to the course for one year and can work through the material and exercises at their own pace. When requested, support is offered to groups or individuals. Following on from the success of this course, an online access course at the following level was developed (SCQF 6 or RQF 3), subsequently followed by a SCQF 7/RQF 4 course. The three online access courses are equivalent to the last three years of the Scottish school education system.

Our awareness for solutions to improve the accessibility of STEM content had increased and since we had had two queries from students with visual impairments, it was time to begin to adapt these courses to ensure their accessibility. We started working on the SCQF 6 course as the skills developed there would help updating the other courses.

The SCQF 6 Mathematics Online Access Course covers: Straight Line, Vectors, Trigonometry, Polynomials, Differentiation, and Integration.

1.2 Quick Tour of Maths Accessibility Research

Much work has been done in recent years to improve the accessibility of teaching methods and resources in Higher Education (CAST, 2024). Most of the current guidance, however, is not suitable for STEM teaching (Cooper, 2012). STEM disciplines rely heavily on mathematical texts, and figures and diagrams which bear pedagogic meaning, rather than being decorative. A specialised framework is therefore necessary. The JISC Accessible Maths Working Group (JISC A11y-Maths group, 2024) has done extensive curative work to collate current results in the domain and has built a community of experts who have developed guidance and resources.

Maths text is usually written either in the typesetting system LaTeX, or in Word, using a maths equation editor. Whilst LaTeX is recognised as best to write advanced mathematical text, it generates PDF documents which are unfortunately not fully accessible: in particular, equations are not compatible with screen reader software (University of Bath, 2026; University of York, 2024). The current advice is to generate documents in HTML format, using the JavaScript MathJax to render the maths, as this will enable compatibility of maths text with screen readers (University of York, 2024; University of Bath, 2026; Cooper, 2012). Both PDF and HTML formats should be made available to students. This can be achieved in various ways. LaTeX files can be converted to HTML using specialist software. Alternative markup languages, such as Quarto (Quarto, 2025), can otherwise be used to simultaneously generate HTML and PDF outputs.

Equation editors in Word, although less performant for writing advanced maths, generate mathematics that is accessible and compatible with screen reader software (Cliffe, 2022; University of York, 2024). However, as shown by Cliffe (2022) and our own results, editors must be used with care to ensure that the maths is indeed accessible.

Figures and diagrams in STEM are often used to illustrate a concept and are seldom simply decorative. The University of Bath has published guidance on producing accessible figures and diagrams, which includes advice on the use of fonts, colours, and legends (University of Bath, 2025). The online dynamic graphing tool, Desmos (Desmos Studio PBC, 2026), creates accessible graphs and geometric figures. GeoGebra (GeoGebra GmbH, 2026) creates less accessible figures but is a more advanced tool. Both tools will generate a permanent URL link to the figure as well as allow for exporting the figure as a PNG file. The recommendation is to use one of these tools to create figures whenever possible, and include the URL, as users can modify the formatting as they need (Cliffe, 2023). Including an alternative description, or a long descriptive caption is good practice: guidance on alternative text for maths graphs is available from DIAGRAM Center (DIAGRAM Center, 2015).

In this paper, we describe the changes we implemented to the SCQF 6 Mathematics Online access course: format and layout of documents (Word, LaTeX and handwritten), figures and diagrams, and amendments to some of the pedagogic approaches. In the following section, we first provide details of the screen reader we have used and explain how we used it to test our new material.

2. Using NVDA Screen Reader

SCQF level 6 access maths course consist of 10 units. The learning materials in each unit included videos, written notes and examples, exercises and solutions. Most of the content was originally written in Microsoft Word using Wiris MathType 7 equation editor and exported as PDFs before uploading to the course area in the Virtual Learning Environment (VLE) Blackboard. Some documents had been written in LaTeX and the exported PDFs uploaded to the VLE. One of our aims was to make the course material accessible to screen reader users. We used NVDA, which is a free, open-source screen reader for the blind and vision impaired available for Windows (NV Access, 2025), for our tests. NVDA is the second most widely used screen reader after the software JAWS developed by the company Freedom Scientific (WebAIM, 2024).

We first ran tests on the original Word documents, which allowed us to identify the NVDA settings required for reading maths written with MathType 7. First, an NVDA add-on is required. Two add-ons are available: MathCAT and Access8Math. We tested both using their default settings and found that the two add-ons can generate different audio outputs of the same maths, as shown in section 3. We also noted that although users can download both add-ons, only one can be activated at a time in NVDA Settings – Math Providers. Second, in NVDA Settings – Advanced, we found that the option “Use UI Automation to access Microsoft Word document controls” must be set to “Only when necessary” for NVDA to read maths written with MathType 7. Third, NVDA users must open one of the equations in the MathType 7 equation editor the first time they read a Word document with NVDA. After this initial step, NDVA will recognise and read maths without requiring the editor to be opened again. Finally, users need an active licence for MathType from Wiris for NVDA to read the maths, as well as to write it.

To overcome the issue of the necessity for a licence to read maths written in MathType 7, we considered using the MathType option to publish Word documents as MathPages. This option allows for Word documents to be exported as HTML, using MathJax to render maths. However, we discovered that not all equations would render with MathJax if the original Word document contained images. Wiris Technical Support confirmed that this was a bug and advised us to remove images from documents. Since many of our documents have images, we decided not to pursue this option further. We also considered using the Wiris MathType Add-in for Microsoft 365. The MathType Add-in converts all maths equations to images and generates alternative text, so screen readers will read the alternative text instead of recognising the equations as maths content. The alternative text generated, however, contained mathml code, which was read verbatim by the screen reader and other text-to-speech tools (Figure). It meant as well that the maths text lost other accessibility features, such as enlargement. Therefore, we did not retain MathType Add-in as a viable accessible option and continued to work with MathType 7. Since our institution does not have an institutional Wiris licence, we checked that funding was available to cover the MathType licence cost for any students who enrolled on the course and required the licence to read the maths.

LaTeX documents were converted to HTML, with MathJax to render maths, using the software LaTeXML (NIST, 2024), and both the PDF and the HTML files were uploaded on the VLE. We also assessed the HTML document with NVDA, which worked well provided one of the maths add-ons was installed.

Since we maintained the original formats of documents, our work focused on improving the accessibility of these formats and devising accessible layout and content. We discuss these in the next section.

Alternative text generated by MathType add-in

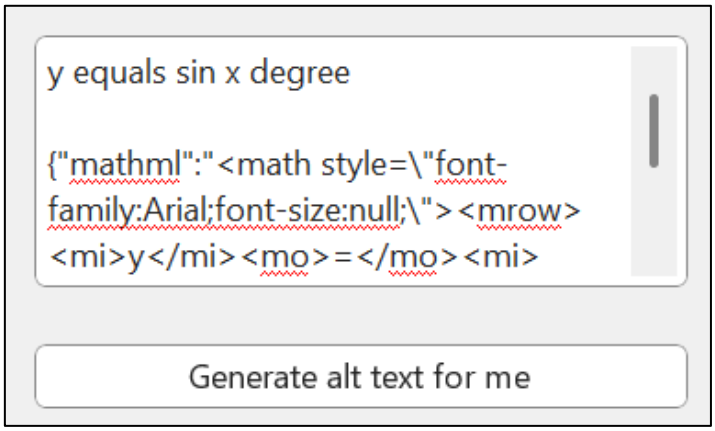


Figure 1: Alternative text pane from a Word document generated by MathType add-in for the maths equation $y = \sin x^{\circ}$.

3. Accessible Digital Maths

3.1 Layout of math content

We audited the accessibility of the original course using the SCULPT framework (Wilson, 2020), Anthology Ally and the built-in accessibility checker of Microsoft, and created a new template for the course. The new template included a new heading structure for navigation within a file using Microsoft Word styles and a new file naming convention for navigation within the course on the VLE.

The template also devised a new heading structure and numbering system for exercises and their subsections, to replace the original lists-based numbering, to ease navigation in exercise and solution sheets. This way, the template clearly differentiated between the various heading levels, including exercises and their answers.

Finally, the template included a new layout for exercises and examples. The original design presented some maths examples and solutions with a combination of horizontal and vertical displays. This affected the reading of maths by the screen reader, as content was recognised as tabular content, and was read row by row. For example, two solutions of a mathematical equation would be commonly displayed in two adjacent columns. The screen reader, however, reads content line by line (Figure). In the new material, we took care to write mathematical steps either exclusively horizontally or vertically. In addition, multistep examples and solutions that included text explanations were embedded in a single MathType object. This improved the flow of reading, compared to using multiple Mathtype objects interspaced with Word text.

3.2 Maths within MathType editor

We aimed to write the maths so that it would be read in a consistent manner throughout documents. We were particularly concerned with this issue, after we discovered that NVDA read maths differently for content written with different maths editors (i.e. Microsoft equation editor vs MathType), if formulas had been added as a figure, and even depending on the maths add-on used with NVDA (MathCAT vs Access8Math). Some of these challenges could be overcome by devising a custom stylesheet in MathType which we applied throughout the course content. This ensured automatic use of formatting styles and improved consistency of maths writing and reading.

However, the use of the stylesheet did not address all issues. We noticed that symbols within MathType must be chosen with care, as they represent specific mathematics operators, and may be read differently in NVDA, even if they may look the same. For instance, at the time of testing in summer 2025, x°, written using the symbol for composition, was read as such, while $x°$ uses the correct degree symbol. Other examples include the decimal point and dot product symbols. All maths had to be scrutinised and manually edited, as this issue had not been identified at the time of creating the course.

Writing multi-steps mathematical work

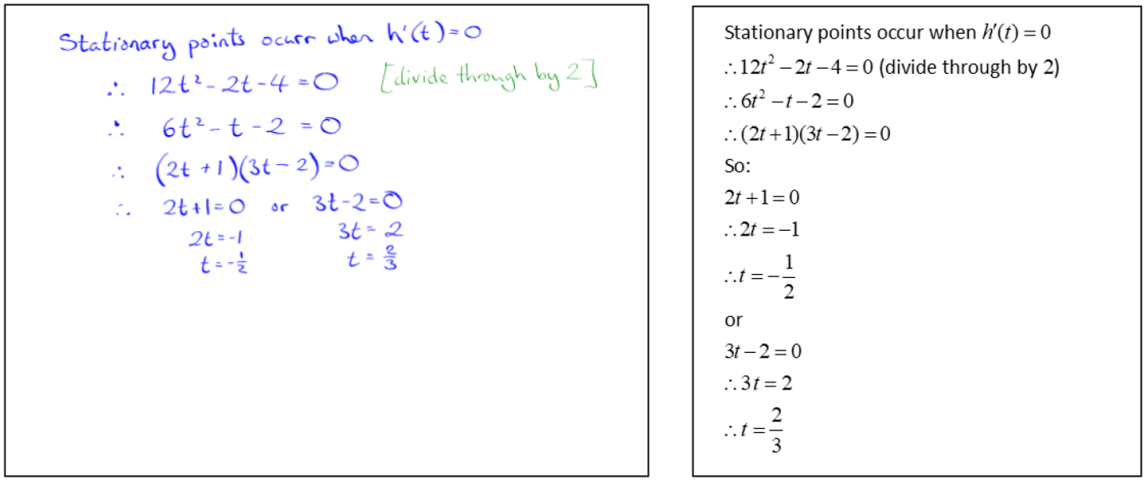


Figure 2: (left) Maths steps are often written as a mixture of horizontal and vertical text, such as the two solutions of an equation. However, the screen reader reads left to write, regardless of reasoning logic (right). Maths steps were re-written systematically vertically. The entire solution is written as a single Mathtype object, not three different objects, for the flow of reading.

Furthermore, some letters can also have different meanings, and may be read differently, depending on MathType style used, as well as the NVDA maths add-on installed. For example, the single, small letter vector notation in STEM could be **u**, $\underline{u}$ or $\vec{u}$. The course team preferred using the notation $\underline{u}$. Unfortunately, $\underline{u}$ was read as 'u below' by NVDA, with both maths add-ons, using their default settings at the time of testing, in summer 2025. The notation **u** was read as 'u' with Access8Math, but as 'atomic mass unit' with MathCAT, and the notation $\vec{u}$ was read as 'vector u' by both add-ons. Given that software and add-on versions and settings can affect the audio output, screen reader users may require support to determine the best settings.

3.3 Maths in LaTeX Documents

Three sections contained documents written in LaTeX: Straight Line, Vectors and Polynomials.

Prior work at the authors' institution had identified LaTeXML (NIST, 2024) as the conversion software that produced most satisfactory outputs (Price et al., 2021). Institutional guidance on using LaTeXML to convert tex documents had been produced and was available.

These documents were short (19 and 11 pages) and given that the maths content was school-level maths, we used LaTeXML with success to convert the tex files to HTML. LaTeXML converts tex files to xml, and converts the xml file to html. We used the following LaTeXML commands:

latexml latex-source-file.tex --dest=intermediate-xml-file.xml

latexmlpost intermediate-xml-file.xml --dest= accesiblehtml-file.html --split --splitat=section --navigationtoc=context --javascript="https://cdnjs.cloudflare.com/ajax/libs/mathjax/2.7.9/MathJax.js?config=TeX-MML-AM_CHTML" --urlstyle=file

The options used in the latexmlpost command generates an html document per section (--split --splitat=section) and a navigable table of contents (--navigationtoc=context). Note that MathJax was loaded using the cdnjs source, as cdn.mathjax.org (used previously) has been retired.

The figures in the original files had all been created using the tikZ LaTeX package. This was the only element that was not converted well by LaTeXML (also noted by Price et al., 2021). All figures, however, were recreated in Desmos, with the PNG export added as a figure to the .tex file, together with a link to the Desmos file in the caption.

3.4 Handwritten Maths

In some cases, maths content was presented as scanned handwritten notes, added as images to Word documents. This was poor from an accessibility standpoint as screen readers could not read the content of the pages. Additionally, the use of handwriting could sometimes be ambiguous, potentially causing confusion between, for example, a multiplication symbol and an x used to denote a variable. The handwritten material was initially manually re-typed in Word with MathType to improve its accessibility. This process was slow and meant that errors could appear due to the ambiguity of some written symbols, particularly when those working on the conversion were not subject experts.

To convert the handwritten content more efficiently while reducing the chance of errors, we experimented with using AI assistants. The authors' institution has a Microsoft licence, so Copilot was initially used. The image file containing the scanned handwritten equations was uploaded and Copilot was asked to generate the content of the images as an equation compatible with MathType. Copilot was unable to carry this out. The prompt was expanded to request that the equations be converted to LaTeX and MathML, but at the time of testing in summer 2025, Copilot was not able to produce a satisfactory output. On discussion with the rest of the team and establishing that there were no risks in using other AI assistants, we used Google's Gemini AI assistant instead. Gemini was able to convert the images quickly and accurately into LaTeX which could then be copied and pasted into the MathType editor (Figure).

While this saved a lot of time, some editing and checks were still necessary. Gemini returned the scanned documents as a continuous string of LaTex code. This was copied and pasted into MathType and then edited for appropriate display. This also allowed for an additional level of sense-checking of the AI assistant's output.

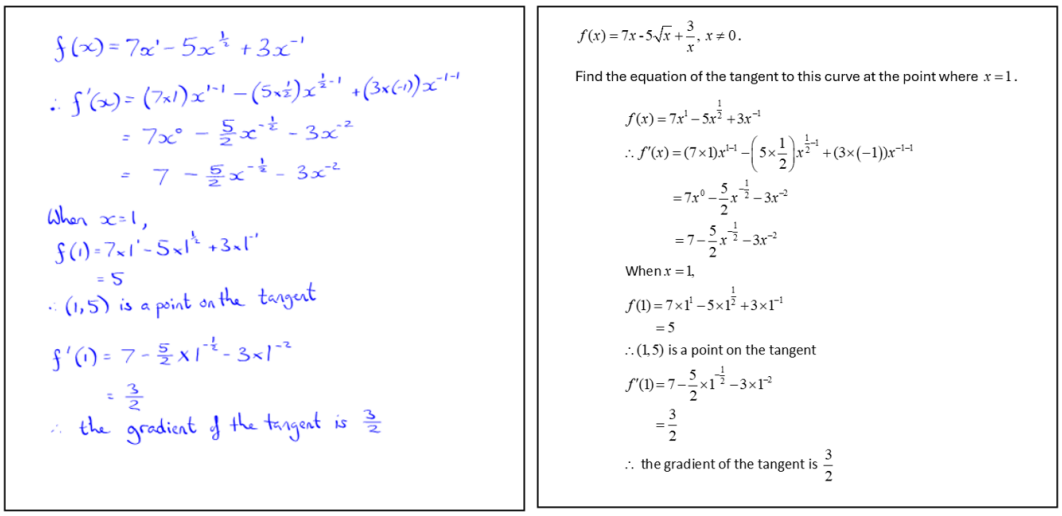


Figure 3: Example of conversion of (left) a handwritten solution to (right) a typed solution, using the Google Gemini AI tool. The image of the handwritten maths was uploaded to Google Gemini, which translated it in LaTeX code. The LaTeX code was copied in the MathType editor in a Word document.

4. Accessible Digital Graphs and Diagrams

We used the Graphing and Geometry tools of Desmos Studio (Desmos Studio PBC, 2026) to create graphs and diagrams, as Desmos generates graphs that are screen reader accessible (Desmos Studio PBC, 2026; University of Bath, 2025). Figures were exported as PNG and a link to the permanent URL was included in the figure captions, in both Word and LaTeX documents (Cliffe, 2023).

4.1 Desmos Geometry Tool

We used the Desmos Geometry tool for figures in the Straight Line and Vectors units and part of the Trigonometry units.

We used a range of objects available in the Geometry library to create the figures. However, since it is not possible to add a label to all types of objects, it was sometimes necessary to use several library functions to create a single object in the way the pedagogic team wished it to appear. For instance, a vector cannot currently be labelled in the Desmos Geometry tool, therefore, to add a label, we either superposed a segment line to a vector object, or added an invisible point object to a vector, as segments and points can be labelled (Figure).

Because of this, the left-hand side expression list sometimes contained several objects that were irrelevant for students and could become a distraction. To avoid this, we used the folder functionality to hide these objects from immediate view. We also used the folder in exercise sheets when the expression was the answer to the exercise to hide the answers from immediate view.

Generating labels in Desmos Geometry

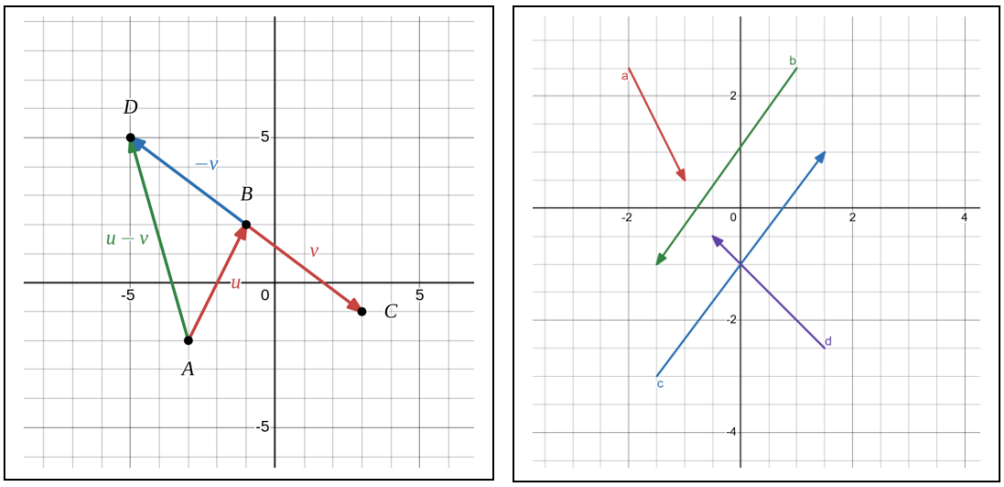


Figure 4: Labelling vectors in Desmos Geometry. To label vectors, either (left) segment lines were superposed to vectors, or (right) invisible points were added to vectors.
See the figures in Desmos: (figure 4 left) and (figure 4 right)

The Geometry tool has a screen reader label option for all objects. We used this option to name and/or describe objects in the figure. For instance, we indicated in the screen reader label when a segment line was a median or an altitude, or when a polygon was a particular figure such as a triangle or rectangle (Figure).

Using screen reader labels in Desmos

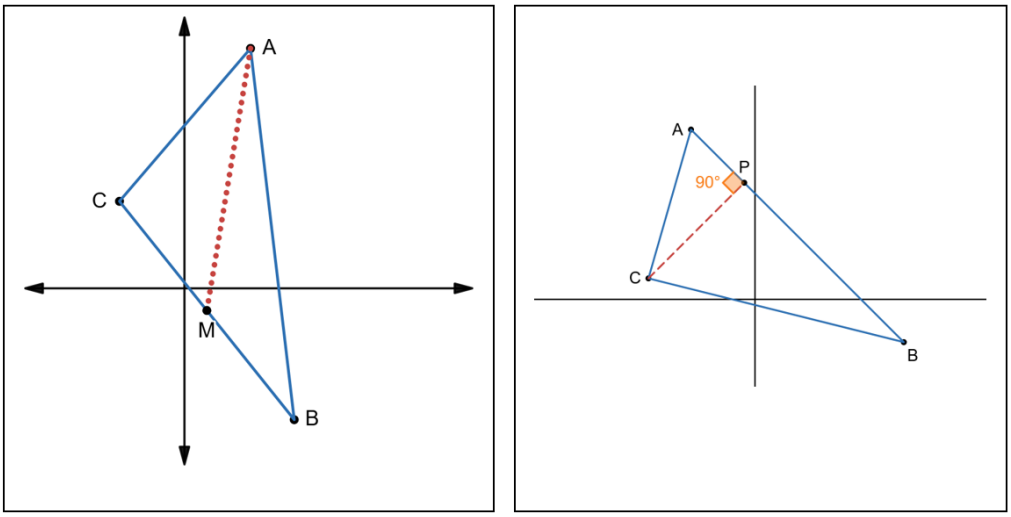


Figure 5: Use of screen reader labels in Desmos Geometry. The screen reader label was used to indicate that the polygon ABC was a triangle (both left and right) and that (left) the segment AM was a median and (right) the segment CP was an altitude.
See the figures in Desmos (figure 5 left) and (figure 5 right)

4.2 Desmos Graphing Tool

The Desmos Graphing tool was used for function graphs in the Trigonometry, Differentiation and Integration units.

In the original course material, figure annotations were included in the Word documents as text boxes overlaying the figure file. In the updated Word documents, we included all figure annotations within the Desmos figures. To annotate graphs, we either created labels by creating an invisible point, following Desmos guidance (Desmos Studio PBC, 2025), or by using the note option on the Graphing tool (Figure). We ensured that graphs could be identified through line type as well as colour (University of Bath, 2025).

Annotating graphs in Desmos

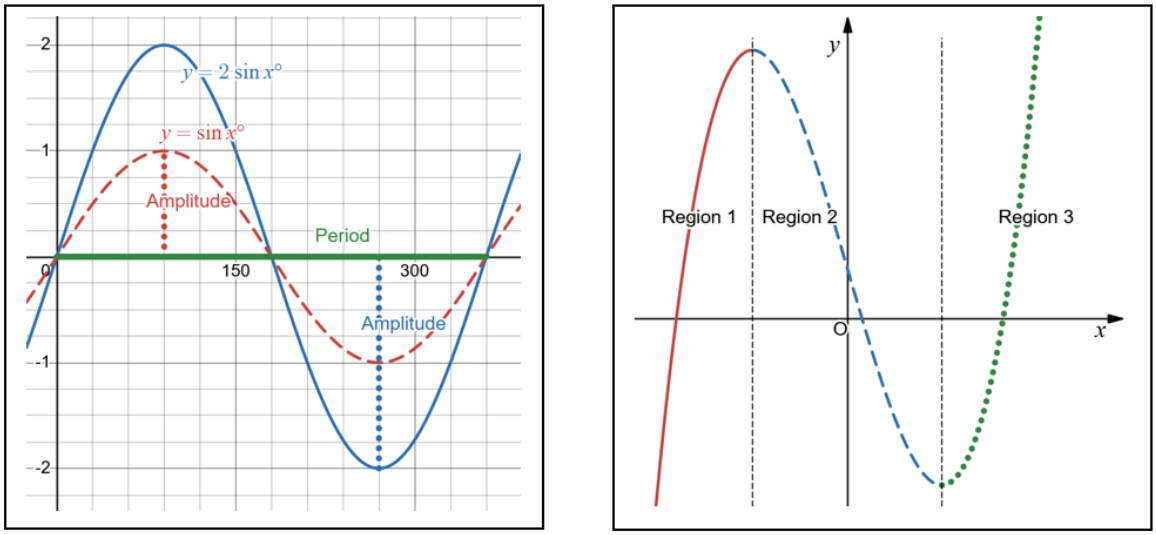


Figure 6: Annotating graphs. We annotated graphs in Desmos, either (left) by using labels of invisible points or (right) by using the note option in Desmos when the annotation was longer. Here the note was used to describe Regions 1, 2 and 3. The note text was also included in the figure caption to ensure that readers who did not access the Desmos link could also get the description.
See the figures in Desmos (figure 6 left) and (figure 6 right).

5. Changing Pedagogy

In some cases, improving the accessibility of the content meant that we had to consider alternative pedagogical strategies, as the updates made using tools such as the Word Template, MathType or LaTeX were not enough to make content accessible. In this section, we describe the three topics that required us to rethink how they were taught.

5.1 Trigonometry: CAST Diagram

The CAST diagram (see Figure) is a common method used in solving trigonometric equations. While this can be highly effective for visual learners, it is not useful for learners who are visually impaired.

CAST diagram

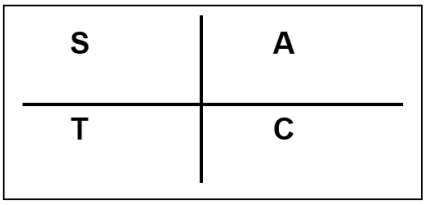


Figure 7: CAST diagram for solving trigonometric equations.

We continued to use the CAST diagram for learners for whom this would be useful, but we added the following detailed alternative description whenever we used it:

In quadrant 1 $\left(0^\circ \text{ to } 90^\circ\right)$, $y = \sin x^\circ$, $y = \cos x^\circ$, and $y = \tan x^\circ$ are all positive.

In quadrant 2 $\left(90^\circ \text{ to } 180^\circ\right)$, $y = \sin x^\circ$ is positive, and $y = \cos x^\circ$ and $y = \tan x^\circ$ are negative.

In quadrant 3 $\left(180^\circ \text{ to } 270^\circ\right)$, $y = \tan x^\circ$ is positive, and $y = \sin x^\circ$ and $y = \cos x^\circ$ are negative.

In quadrant 4 $\left(270^\circ \text{ to } 360^\circ\right)$, $y = \cos x^\circ$ is positive, and $y = \sin x^\circ$ and $y = \tan x^\circ$ are negative.

This provided students with both pictorial and descriptive explanations of the CAST diagram.

5.2 Polynomials: Synthetic Division

When solving polynomials, synthetic division is often used (see Figure).

Polynomial division

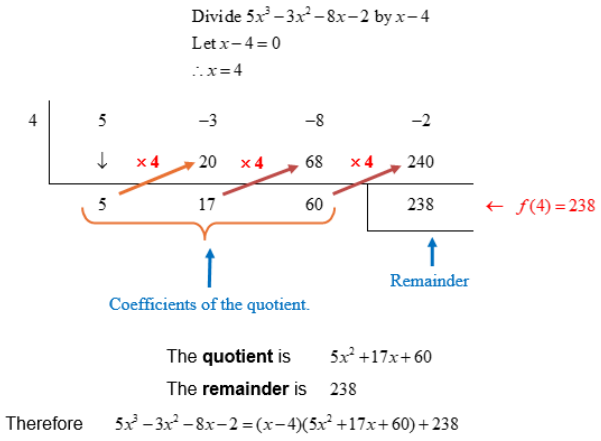


Figure 8: Example of polynomial division, as taught in the online maths access course. The information flow is both vertical and horizontal, and text boxes overlay the table.

This presents information that flows both vertically and horizontally. It also uses elements such as arrows and curly brackets in text boxes overlaying the table and therefore cannot be picked up by a screen reader. In discussion with Sight Scotland and the Royal Blind School (Sight Scotland, 2025), we devised an alternative way of teaching synthetic division in table form.

Polynomial division: accessible alternative

Accessible version of remainder theorem

Divide $5x^3-3x^2-8x-2$ by $x-4$ $\therefore$ Let $x-4=0$ $\therefore$ $x=4$

term from highest to lowest powers	coefficient	when $x=4$	answer	Quotient term
$5x^3$	5	copy coefficient of highest term	$=5$	$5x^2$
$-3x^2$	-3	$5\times4+(-3)$	$=17$	$17x$
$-8x$	-8	$17\times4+(-8)$	$=60$	60
-2	-2	$60\times4+(-2)$	$=238$	Remainder 238

The **quotient** is $5x^2+17x+60$

The **remainder** is 238

Therefore $5x^3-3x^2-8x-2=(x-4)(5x^2+17x+60)+238$

Figure 9: Alternative accessible presentation of the polynomial division. No overlaying text box is used, and the information flows in rows.

The information is presented in a table and is organised in agreement with the screen reader's direction of reading (by rows).

5.3 Calculus: Curve Sketching and Nature Table

In calculus the nature of stationary points can be determined with a nature table (see Figure).

Using the nature table to determine stationary points

The curve $y=\frac{x^3}{3}+\frac{5x^2}{2}-6x+5$ has a stationary point when $x=-6$. Determine the nature of this stationary point.

x	$\rightarrow$	-6	$\rightarrow$
$\frac{dy}{dx}$	positive	0	negative
Shape	/	—	\

Therefore, there is a **maximum stationary point** at $(-6, 59)$

Figure 10: Example using the nature table.

The nature table is very pictural and can be particularly useful for visual learners, but inaccessible to visually impaired learners. The order in which the information would be read in such a table is also, again, problematic. Therefore, for every traditional nature table, we added an accessible version of the table, which reversed the way in which the information was laid out, and did not make use of pictural symbols (see Table 1).

Table 1: Accessible nature table

x	$\frac{dy}{dx}$	Shape
$x < -6$	positive	increasing
$x = -6$	0	stationary
$x > -6$	negative	decreasing

6. Conclusion

In this paper, we describe the work we did to improve the accessibility of an online access maths course. The maths content is at foundation level, and many of the topics taught are covered in university foundation maths courses. Therefore, our results are also relevant to HE practitioners. The course originally consisted of PDF documents generated from Word or LaTeX. Word PDFs have all been replaced by accessible Word documents, and LaTeX PDFs have all been uploaded together with alternative HTML documents.

Extensive work has been done in recent years on digital solutions for mathematical and STEM content. Our own work greatly benefited from this research: we used current guidance on how to ensure maths is readable by screen readers and how to design figures and diagrams. We were also able to provide an accessible alternative to LaTeX documents quickly and efficiently.

We have also uncovered some issues that STEM teachers must pay attention to. Using an equation editor in Word documents does not necessarily make equations accessible. Symbols must be used with care for the maths to be read accurately. Additionally, thought must be given to the layout of exercises, and maths within exercises, to ensure that documents, either Word or LaTeX, can be navigated easily, and maths read in a sensible manner.

All tests were carried out on Windows operating systems, as our institution has a Microsoft licence. We noted that neither NVDA nor JAWS, another popular screen reader software, are available for Mac. To our knowledge, Mac VoiceOver does not have add-ons for handling maths content. We suggest, therefore, that more investigation is done for Mac operating systems.

Making STEM content accessible is not straightforward and requires expert knowledge and skills. Nonetheless, it is essential if we are to ensure that STEM courses are accessible to all. We hope that, with this work, we have contributed to this young, dynamic and important area of research.

7. Appendix: Project Workflow

The original course consisted of 174 PDF files, generated either from Word documents or from LaTeX documents, 15 of which were scans of hand-written material. Documents were short: the Word-PDFs were less than 10 pages, and the LaTeX-PDFs less than 20 pages.

The reviewed course consists of:

- 123 accessible Word documents using the new template, devised as described in section 3, and MathType 7 for writing all maths.
- 12 documents in both LaTeX-PDF and HTML with MathJax to render maths text.

The course also contained 104 images which were all re-designed in Desmos, with all annotations included in the Desmos file, as described in section 4.

The project team consisted of 2 eLearning advisors, 3 students employed as eLearning support assistants, 1 eLearning lead advisor, 1 University maths support advisor, and the course coordinator. The eLearning advisors and eLearning support assistants worked on Word documents, Desmos figures and hand-written documents. The eLearning lead advisor managed the timeline of the project, general accessibility issues, and worked on the NVDA settings. The maths support advisor worked on LaTeX documents and managed mathematics and STEM specific accessibility issues. The course coordinator worked on pedagogy and approved the final course documents.

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CASE STUDY

Improving Mathematical Confidence in Biosciences Through Contextualised Support: A Two-Year Initiative

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Abstract

Many undergraduate biosciences students enter university with limited mathematical preparation, often having last studied mathematics at GCSE level and perceiving it as irrelevant to their discipline. This case study describes a two-year teaching initiative at Queen Mary University of London designed to improve mathematical confidence and competence among biochemistry, biology, zoology, and medical genetics students. Following diagnostic testing and collaboration with laboratory instructors, contextualised mathematics workshops were developed and aligned with laboratory experiments covering unit conversions, molarity, dilutions, and data interpretation. The programme evolved from bi-weekly sessions in Year 1 to weekly, lab-aligned workshops with scaffolded resources in Year 2. Results demonstrated improvements in diagnostic test performance and suggested improved confidence among workshop attendees, though attendance patterns revealed challenges with student engagement during assessment-heavy periods. The findings highlight both the benefits and challenges of voluntary contextualised mathematics support within biosciences education.

Keywords: Mathematics literacy, biosciences, contextualised support, student confidence, laboratory skills.

1. Introduction

Students in bioscience disciplines frequently encounter unexpected mathematical challenges during undergraduate studies, particularly when laboratory modules require fluency in unit conversions, solution preparation, dilutions, and quantitative data interpretation. The concern about mathematical competency has grown in recent years, with technological advances making biosciences increasingly quantitative (Durán and Marshall, 2019). This was formally recognised in 1995 through a report coining the term ‘Mathematics Problem’ (LMS et al., 1995).

Many bioscience students enter university with limited recent mathematical experience. Hillman (2014) reports that only 28% of biosciences students have taken A-Level mathematics, with the majority completing mathematics only to GCSE level. In the UK, GCSE (General Certificate of Secondary Education) is taken at age 15–16, whilst A-Levels (Advanced Levels) are the pre-university qualifications taken at age 17–18. This contributes to perceptions that mathematics is not central to biological sciences, leading to difficulties when mathematical skills are required (Hester et al., 2014). Research demonstrates that students face problems with mathematical aspects of their degrees, unable to use quantitative skills to solve biology problems (Hester et al., 2014; Tariq, 2008; Bowyer and Darlington, 2018).

This case study presents a two-year initiative to address these challenges through contextualised mathematics support for first-year biosciences students: Year 1 (2022–23) served as a pilot phase focusing on programme development and refinement, whilst Year 2 (2023–24) involved systematic data collection including pre- and post-diagnostic testing, attendance tracking, and formal evaluation of the refined programme.

At Queen Mary University of London (QMUL), the School of Biological and Behavioural Sciences (SBBS) identified mathematics literacy as a priority enhancement area. Many students entering programmes in biochemistry, biology, zoology, and medical genetics have limited recent mathematical experience, with most having completed mathematics only to GCSE level. This was reinforced through my experience teaching foundation mathematics and through reports from module organisers about students' inability to perform basic calculations in first-year laboratory experiments for courses BIO190 (Practical Molecular and Cellular Biology) and BCH198 (Practical Biochemistry). Following consultation with my mentor Dr Ewan Main and module organisers, we developed mathematics support sessions tailored to first-year biosciences students, aiming to improve computational skills, build confidence, and demonstrate mathematics relevance within biological contexts.

2. Context and Literature

Mathematics support for students in non-mathematics disciplines has gained increasing attention in higher education. Lawson et al. (2019) highlight key themes including student non-engagement and support positioning within programmes. Research demonstrates that many science students struggle with mathematical concepts due to anxiety, lack of confidence, and difficulty seeing abstract procedures' relevance (Wachsmuth et al., 2017).

Contextualised teaching—embedding mathematical concepts within discipline-specific examples—has been shown to improve engagement and learning outcomes (Beswick, 2011). Koenig (2011) reported that mathematics anxiety drastically affects confidence and motivation, though embedding mathematics in biological contexts helps address both.

Maths anxiety — defined as feelings of tension and apprehension that interfere with mathematical problem solving (Ashcraft and Kirk, 2001) — is a well-documented phenomenon among undergraduate science students. Wachsmuth et al. (2017) demonstrated that many biology students harbour negative emotions towards mathematics that go beyond simple disengagement. Such anxiety can manifest as avoidance behaviour, reluctance to attempt problems, and expressions of helplessness — patterns observed informally among students in the present study, who frequently expressed sentiments such as "I don't want to do maths" or "I always find it hard." Contextualised teaching within biological settings has been shown to help mitigate these responses by making mathematics feel more relevant and less threatening (Koenig, 2011).

The timing of mathematical challenges is critical; students benefit from "just-in-time" support aligning with when they need specific skills (Jackson and Johnson, 2013). Studies of undergraduate biochemistry students have similarly identified difficulties with topics requiring mathematical skills, highlighting the need for targeted support (Watters et al., 2022). The Quality Assurance Agency Subject Benchmark for Biosciences (2023) explicitly states that mathematics is a core requisite, with manipulation of equations, problem solving, and statistical analysis crucial to the degree.

3. Programme Design and Development

3.1. Baseline assessment and learning outcomes

Prior to launching support sessions, baseline assessment was conducted through questionnaires and diagnostic testing. Results indicated that 99% of students had completed GCSE mathematics, whilst 56% had studied mathematics at A-level. Despite this, only 42% reported feeling confident in their mathematical abilities, as measured through a baseline questionnaire administered at the start of the programme, which included the item: "How confident do you feel in your mathematical abilities?" (see Section 4 and Appendix A). The programme was open to all first-year students enrolled in BIO190 (Practical Molecular and Cellular Biology) and BCH198 (Practical Biochemistry),

covering undergraduate degrees in Biology, Zoology, Biochemistry, and Medical Genetics, as illustrated in Figure 1.

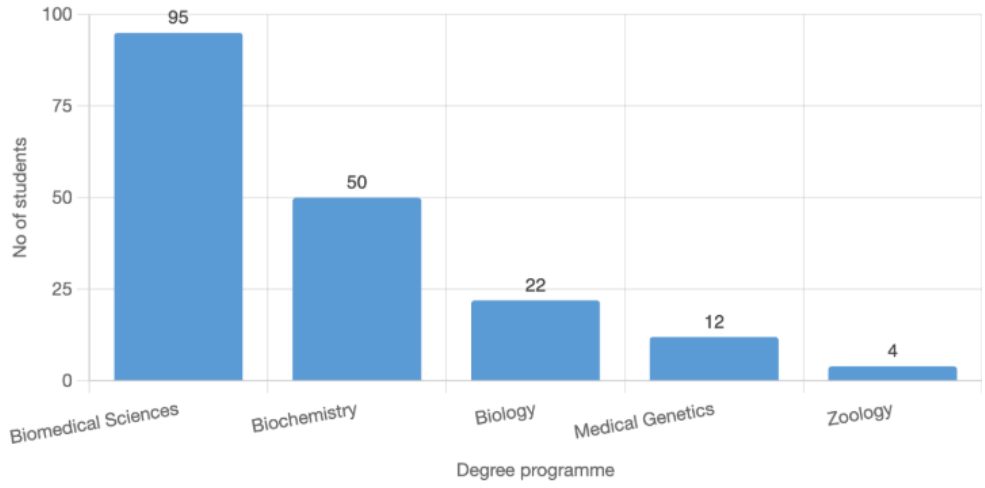


Figure 1. Distribution of students across biosciences degree programmes participating in the mathematics support programme.

The programme was structured around five core learning outcomes aligned with mathematical requirements of laboratory modules BIO190 and BCH198:

- Perform arithmetical calculations including unit conversions and precision;
- Calculate materials and solutions including molarity and dilutions;
- Manipulate and simplify algebraic and numerical expressions;
- Solve and develop equations using variables;
- Create and analyse graphs relating to different relationships.

These learning outcomes were aligned with SBBS categories to ensure curricular coherence and emphasise analytical skills development.

3.2. Year 1 implementation

The first year consisted of five one-hour sessions delivered every two weeks at 9:00 am, voluntary for all first-year biosciences students. The format centered on solving exercise sheets with brief introductions followed by guided practice.

Topics covered included: Units and Scientific Notation; Molarity and Dilutions; Numerical and Algebraic Expressions; Variables and Equations; and Graphs.

Initial implementation faced challenges. The bi-weekly schedule made it difficult to maintain momentum and alignment with concurrent laboratory activities. The one-hour format proved insufficient given the range of student abilities. Attendance declined across the five sessions, with students citing timing issues, competing commitments, and varying perceived need.

3.3. Year 2 enhancements

Based on Year 1 feedback and insights from the CETL-MSOR 2022 conference, significant changes were implemented. Sessions were restructured to run weekly, and topics were sequenced to align with laboratory experiments. This “just-in-time” approach ensured students learned mathematical concepts immediately before needing them practically.

Worksheets were redesigned to include three difficulty levels: basic "self-check" questions, standard problems aligned with laboratory requirements, and advanced challenge problems. This scaffolded approach better accommodated diverse mathematical backgrounds.

A dedicated QMplus page (Queen Mary University of London's online learning environment, available at https://qmplus.qmul.ac.uk) was established hosting all materials, additional resources, and optional online quizzes using Numbas (an open-source e-assessment system for mathematics; https://www.numbas.org.uk; Sangwin and Hunt, 2019). Plans were developed to incorporate short instructional videos for viewing before sessions. Students were encouraged to work collaboratively, and session timing was adjusted to later morning slots (around 11:00 am).

Throughout development, ongoing collaboration with module organisers ensured alignment between workshop content and laboratory requirements.

4. Evaluation Methods

The Year 2 programme was evaluated through multiple methods, following approaches recommended by MacGillivray and Croft (2011), who advocate triangulating multiple data sources rather than relying on any single measure. Patel and Little (2006) similarly emphasise the importance of measuring the impact of mathematics support through multiple indicators. Accordingly, data were collected through five complementary methods: diagnostic testing at programme start and end; attendance tracking across all sessions; questionnaires measuring confidence and perceived relevance; qualitative feedback through surveys and weekly QMplus comments; and informal discussions with students and colleagues.

The confidence and perceived relevance questionnaire was developed by the author based on the programme's learning outcomes and objectives and reviewed by mentor Dr. Ewan Main prior to administration. The full questionnaire is provided in Appendix A.

This study involved the routine evaluation of an educational support programme using anonymised, aggregated data. Participation in all questionnaires and diagnostic tests was voluntary, and students were informed at the outset that aggregated data may be used for evaluation and publication purposes. No individual students are identifiable in any output. This project was reviewed by the Queen Mary University of London Research Ethics Committee, which confirmed that no further ethical review is required (Reference number: QME26.2471, 11 May 2026).

The diagnostic test consisted of 20 questions covering core mathematical skills required for laboratory work, providing baseline and post-programme measures.

5. Results

5.1. Diagnostic test performance

An identical 20-question diagnostic test was administered at the start and end of the Year 2 programme (2023–24) to assess mathematical competence. Initial testing was conducted in September 2023 (n=185), whilst post-programme testing took place in December 2023 (n=110).

Initial testing revealed variation in mathematical preparedness, with 100 students (54.1%) scoring in the 0-10 range out of 20, indicating substantial areas requiring support.

Following the intervention, post-programme diagnostic testing showed clear descriptive improvements. Figure 2 illustrates the pre- and post-test score distributions side-by-side, demonstrating a shift towards higher performance. The proportion of students in the lowest

performance range (0-10) decreased from 54.1% to 18.2%, whilst the proportion in the highest range (16-20) increased from 10.8% to 27.3%.

As participation in both the pre- and post-diagnostic tests was voluntary, and the number of students completing each test differed (n=185 pre-test; n=110 post-test), it was not possible to conduct a matched-student analysis linking individual scores across both time points. This represents a limitation of the evaluation design. Statistical significance tests were not performed, as this study constitutes routine educational evaluation rather than formal research; results are therefore presented descriptively and should be interpreted with caution. Future iterations of the programme will incorporate anonymous but traceable identifiers and be designed with full ethical approval from the outset, enabling paired comparisons and more rigorous statistical evaluation.

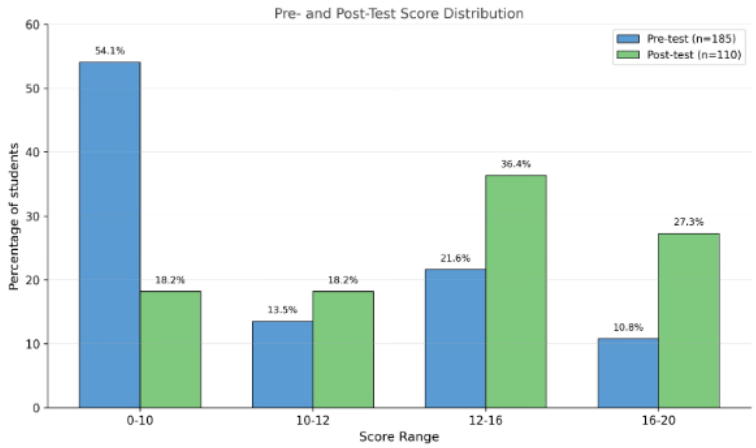


Figure 2. Pre- and post-test score distribution showing improvement in mathematical competence (n=185 pre-test, n=110 post-test).

5.2. Attendance patterns

Attendance data revealed clear engagement patterns across both years, with Figure 3 illustrating the comparative attendance trends for Year 1 (2022–23) and Year 2 (2023–24).

In Year 1, a consistent and steep decline was observed across the five bi-weekly sessions. Attendance began at 48 students in Session 1, declining to 27 students in Session 2, 16 students in Session 3, 12 students in Session 4, and 11 students in Session 5. This decline was particularly pronounced after Session 3, which preceded Week 7 — the university's designated reading week (a mid-semester break with no timetabled classes) — after which attendance did not recover.

In Year 2, the expanded programme of eight weekly sessions showed markedly improved engagement compared to Year 1. Initial attendance was considerably higher, beginning at approximately 60 students in both Sessions 1 and 2, before declining to approximately 45 students in Session 3 and 30 students in Session 4. Attendance then stabilised gradually, with approximately 25, 23, 22, and 20 students attending Sessions 5 through 8 respectively. Whilst a decline was still observed, the pattern was considerably less steep than in Year 1, suggesting that the enhancements introduced in Year 2 — including weekly scheduling, later morning timing, scaffolded worksheets, and improved alignment with laboratory activities — had a positive effect on both initial engagement and longer-term retention.

Qualitative feedback across both years revealed multiple factors contributing to declining attendance including competing commitments and varying perceived need. Some students felt confident after initial sessions and discontinued attendance, whilst others found the pace challenging.

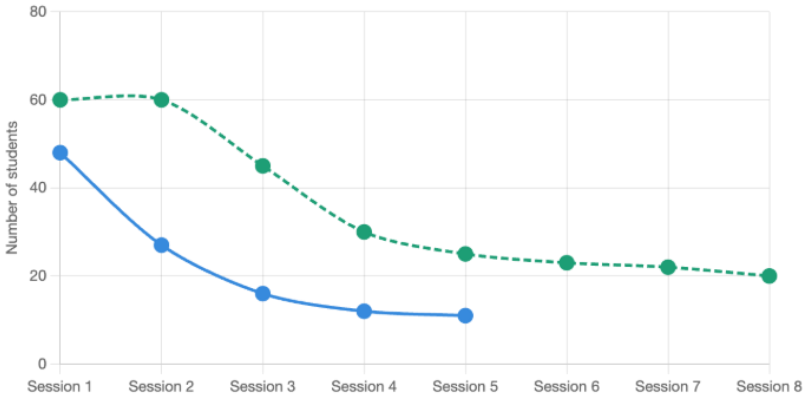


Figure 3. Attendance comparison across Year 1 (2022–23) and Year 2 (2023–24) mathematics support sessions.

5.3. Confidence and qualitative feedback

The results presented in this section relate primarily to Year 2 (2023–24), as Year 1 (2022–23) served as a pilot phase focused on programme development and refinement rather than systematic data collection. Baseline questionnaire responses from Year 2 indicated that 42% of students reported feeling confident in their mathematical abilities at programme start. Whilst no formal post-programme confidence questionnaire was administered, qualitative feedback collected from Year 2 workshop attendees through weekly QMplus comments and informal discussions suggested improved confidence among attendees, with students expressing greater comfort with laboratory calculations and unit conversions. This represents a limitation of the evaluation, as confidence data was not systematically collected using the same instrument post-intervention.

Formal end-of-programme evaluation revealed both appreciation and suggestions for enhancement. Representative comments included:

- “I am grateful for this class as a below average student in maths. It was really helpful”;
- “More questions”;
- “More interaction”;
- “More convenient time than 9am”;
- “More online quizzes”;
- “More session on graphs and analysing them”.

These comments reflect both positive impact and practical barriers affecting sustained engagement. Some explicitly stated they stopped attending because they had achieved their goals, suggesting the intervention succeeded in building confidence.

6. Discussion

The mathematics support programme demonstrated both successes and challenges common to voluntary initiatives. The contextualised approach—embedding mathematical concepts within biosciences applications and aligning sessions with laboratory activities—was effective in improving student confidence and competence for those who engaged, aligning with research showing that embedding mathematics in biological contexts helps motivation (Koenig, 2011).

The shift from bi-weekly to weekly sessions in Year 2, combined with improved laboratory schedule alignment, represented significant enhancement, implementing the “just-in-time” support model

(Jackson and Johnson, 2013). Scaffolded worksheets better accommodate the diverse cohort, whilst online resources provide valuable flexibility.

However, declining attendance presents an ongoing challenge. Whilst some attrition resulted from students achieving their goals, the 77% decline in Year 1 attendance from Session 1 to Session 5 (as shown in Figure 3) suggests competing pressures during assessment periods deterred students precisely when consolidation might be most valuable, reflecting broader challenges about life sciences students' attitudes towards mathematics (Wachsmuth et al., 2017). Despite improvements in Year 2, sustained attendance remained a substantial challenge, indicating that structural barriers and perceptions surrounding mathematics support persisted.

Maths anxiety is also likely to have played a role in both attendance patterns and student engagement. Informal observations during sessions revealed that several students exhibited classic indicators of maths anxiety, including reluctance to attempt problems independently and verbal expressions of fear or helplessness towards mathematics. Diagnostic tests may not fully capture student competence in the presence of anxiety, as performance under test conditions can be adversely affected by anxiety responses (Ashcraft and Kirk, 2001). The contextualised, low-stakes workshop environment was designed in part to address this by embedding mathematics within familiar biological contexts and encouraging collaborative working. Managing productive struggle and the emotions associated with learning mathematics is an important pedagogical consideration (Wachsmuth et al., 2017). Facilitators should be attentive to signs of anxiety and respond with encouragement rather than correction, fostering a growth-oriented rather than performance-oriented classroom culture.

The difficulty obtaining post-programme diagnostic test completion reflects challenges in evaluating voluntary support interventions (MacGillivray and Croft, 2011). The diverse mathematical backgrounds—ranging from those who found sessions too easy to those who struggled—highlights challenges that lack of mathematical knowledge adds to learning science (Park and Choi, 2013).

The findings suggest that whilst voluntary, contextualised mathematics support can be effective, consideration should be given to embedding some mathematical skill development directly within core modules to ensure all students receive necessary support. The workshops can supplement embedded provision, providing additional practice for those who seek it.

7. Future Developments

Based on two years of implementation, several enhancements are planned:

- Integration of LearnSci Smart Worksheets (interactive digital worksheets providing immediate feedback; https://learnsci.com) for more dynamic student engagement;
- Development of instructional videos (MathsCasts) for viewing before sessions, following evidence that such resources effectively complement in-person mathematics support (Loch et al., 2012);
- Implementation of centralised attendance tracking to identify students needing targeted outreach;
- Introduction of completion certificates to recognise participation;
- Improved signposting regarding workshop benefits;
- Exploration of curriculum embedding within laboratory modules;
- Reordering topics to begin with molarity and dilutions;
- Continued use of interactive tools such as Mentimeter (a live audience response platform enabling real-time polls and quizzes; https://www.mentimeter.com);

- Careful attention to feedback design, ensuring that feedback on mathematical performance promotes a growth mindset and builds confidence without exacerbating existing anxiety, in line with recommendations from Wachsmuth et al. (2017).

Future work will explore whether targeting the programme specifically at students scoring below 60% on diagnostic tests improves engagement and impact. Materials will be disseminated through incorporation into foundation mathematics course SEF040 (Foundation Mathematics) redesign, sharing with Peer-Led Team Learning (PLTL) sessions — a structured collaborative learning model in which trained student peers facilitate small group problem-solving workshops (Cracolice and Deming, 2001) — and presentation at conferences and in academic journals.

8. Conclusion

This case study demonstrates that contextualised mathematics support aligned with laboratory activities can improve confidence and competence in biosciences students, addressing the recognised challenge of mathematical literacy in life sciences education. The iterative development, responding to student feedback and insights from educational literature, highlights the importance of flexibility and responsiveness in designing support interventions.

Whilst voluntary support sessions face inherent challenges with sustained engagement—particularly given attitudes of many bioscience students towards mathematics—they serve an important role in providing targeted help to students who recognise their need for mathematical skill development. The combination of in-person workshops, online resources, and scaffolded materials accommodates diverse learning preferences and ability levels.

The programme's evolution from loosely structured bi-weekly sessions to weekly, lab-aligned workshops with multi-level resources demonstrates the value of action research approaches in educational development. Moving forward, a blended approach combining embedded mathematical skill development within core modules with voluntary enhancement workshops may offer the most comprehensive support, ensuring all students develop essential quantitative skills whilst providing additional resources for those seeking deeper understanding or facing particular challenges. The study highlights the importance of contextualised, responsive, and discipline-integrated mathematics support in improving engagement with quantitative skills in biosciences education.

Appendix A: Prior Knowledge Questionnaire 2023/2024

The following questionnaire was administered to all first-year biosciences students at the start of the Year 2 programme (2023–24) to assess prior knowledge, confidence, and attitudes towards mathematics.

1. What degree programme are you enrolled in?

2. What is the highest level of maths you have studied?

- GCSE / IGCSE / O-level
- A-level / IB / equivalent
- University-level maths
- Other

3. When was the last time you studied maths formally?

- Less than 1 year ago
- 1–2 years ago
- 3–5 years ago
- More than 5 years ago

4. How important do you think mathematics is for your degree?

- Very important
- Important
- Somewhat important
- Not important

5. How would you rate your overall confidence in your mathematical skills?

1 = Not confident at all 2 3 4 5 = Very confident

6. How confident are you in the following topics? (1 = Not confident at all, 5 = Very confident)

- Units and Conversions
- Numerical and Algebraic Operations
- Equations
- Graphs and Data Interpretation

7. Are you interested in improving your mathematical literacy?

Yes No

8. What challenges do you face when learning mathematics? (tick all that apply)

- Anxiety or lack of confidence
- Difficulty keeping up with pace of teaching
- Lack of practice opportunities
- Not seeing relevance to my degree
- Other

9. What type of support would be most useful to you? (tick all that apply)

- Revision of core topics
- Help with maths applied to biosciences (e.g., molarity, graphs, statistics)
- Practice questions / worksheets
- Online resources (videos, quizzes, tutorials)
- Drop-in sessions / one-to-one support
- Exam preparation

10. Which areas of your degree do you think will use mathematics the most?

- Chemistry / lab calculations
- Data analysis / statistics
- Physics / biomechanics
- Other

11. Why would you like to improve your maths skills?

- To pass exams
- To improve lab work
- For career development
- For general confidence
- Other

12. Is there anything else you would like us to know about your experience with maths?

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CASE STUDY

Embedding algorithmic thinking into 1st year undergraduate programmes

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Abstract

We describe the embedding of algorithms and algorithmic thinking into a first-year undergraduate pure mathematics course at the London School of Economics (LSE). Responding to growing demand for computational thinking skills, we redesigned 'Introduction to Abstract Mathematics' to integrate algorithmic approaches throughout the curriculum rather than as an isolated topic. Using the Knowledge, Skills and Behaviours (KSBs) framework adapted from degree apprenticeships, we developed learning outcomes that distinguish knowing algorithms from thinking algorithmically. Our approach reformulates traditional proofs using constructive and algorithmic methods, introduces loop invariants alongside mathematical induction, and shows how algorithms can both prove mathematical statements and have their own properties proven.

Keywords: Algorithmic thinking, threshold concepts, curriculum design, computational thinking, learning outcomes.

1. Introduction

Algorithms shape everyday life, from social media recommendation systems to financial trading platforms (Cormen et al., 2022; O'Neil, 2016). Meanwhile, the graduate job market is more competitive than ever, with employers increasingly seeking strong analytical and computational thinking skills (High Fliers Research, 2024; CBI/Pearson, 2023). Computational thinking has become essential across disciplines, and embedding it in mathematics education can enhance students' problem-solving and deepen their understanding of mathematical structures (Lockwood et al., 2016; Weintrop et al., 2016).

This work sits within a broader movement to modernise mathematics education for the 21st century. The increasing mathematisation of social sciences, particularly at LSE where economics, finance, and data science dominate, demands that pure mathematics courses evolve while maintaining their foundational role. Our approach addresses this challenge by treating algorithmic thinking not as an addition to the curriculum, but as a fundamental way of engaging with mathematical concepts.

Our intervention has three key features:

1. We integrate algorithmic thinking throughout the course rather than as an isolated topic;
2. We maintain focus on mathematical reasoning without requiring specific programming skills;
3. We explicitly distinguish knowledge of algorithms from the development of algorithmic thinking as a mathematical practice.

2. Theoretical Framework

2.1. Algorithms as threshold concepts

Our approach is grounded in the threshold concepts framework developed by Meyer and Land (2003, 2006). Threshold concepts are transformative ideas that, once understood, fundamentally change how students perceive and practice within a discipline. They are characterised as being

transformative, irreversible, integrative, bounded, and often troublesome for learners. We propose that algorithmic thinking represents a threshold concept in mathematics education for several reasons:

1. Transformative: Understanding algorithms transforms how students approach existence proofs and constructions; once they grasp that proving something exists can be achieved by constructing it algorithmically, their whole approach to such problems changes;
2. Irreversible: Once acquired, algorithmic thinking is difficult to unlearn; students report being unable to view mathematical problems without considering algorithmic solutions;
3. Integrative: Algorithmic thinking connects previously disparate areas; number theory, linear algebra, and group theory share common algorithmic threads that expose hidden connections;
4. Bounded: Algorithmic thinking has clear boundaries within mathematics, distinguishing it from both pure abstraction and mere calculation.

Framing algorithmic thinking as a threshold concept has direct consequences for teaching. Because the concept is *integrative* (drawing together number theory, linear algebra, and group theory) it is poorly served by isolated treatment - its connective power becomes visible only when encountered repeatedly across topics. And because crossing the threshold is *transformative* and often *troublesome*, students need sustained, scaffolded exposure rather than a single dedicated unit. These observations motivate the central design decisions of the next section: distinguishing knowing algorithms from thinking algorithmically, and embedding the latter throughout the course rather than as a standalone topic.

2.2. Constructivism and algorithmic thinking

Our pedagogical approach is rooted in constructivist learning theory (Piaget, 1952; Vygotsky, 1978), which holds that learners actively build knowledge through experience and reflection rather than receiving it passively. Algorithmic thinking aligns naturally with this: when students develop algorithms, they literally construct mathematical objects. The Extended Euclidean Algorithm, for example, does not merely prove Bézout's Identity exists, it constructs the coefficients. Such active construction helps students internalise abstract concepts through concrete manipulation.

Following Vygotsky's Zone of Proximal Development (ZPD), we use algorithms to scaffold learning. Their step-by-step nature provides intermediate stages between what students can do independently and what they can achieve with guidance; loop invariants, for instance, scaffold the transition from computational verification to formal proof.

The integration of algorithmic thinking supports movement through Bloom's Revised Taxonomy (Anderson and Krathwohl, 2001), as presented in Table 1.

Notably, algorithmic thinking provides concrete pathways to higher-order skills: creating an algorithm (the highest level) becomes accessible earlier than creating proofs, giving students success experiences that build confidence and motivation.

Table 1. Bloom's level, traditional approach and algorithmic enhancement

Bloom's Level	Traditional Approach	Algorithmic Enhancement
Remember	Memorise theorem statements	Recall algorithm steps
Understand	Explain proof logic	Trace algorithm execution
Apply	Use theorems in problems	Execute algorithms on examples
Analyse	Decompose proof structure	Analyse algorithm complexity
Evaluate	Assess proof validity	Compare algorithm efficiency
Create	Construct new proofs	Design new algorithms

3. Learning Outcome Design

Building on this foundation, we adopted an approach to learning outcomes taken from degree apprenticeships: Knowledge, Skills and Behaviours (KSBs) (Institute for Apprenticeships and Technical Education, 2023). The KSB framework aligns well with the Quality Assurance Agency (QAA) Subject Benchmark Statement for Mathematics, Statistics and Operational Research (QAA, 2023), which emphasises both subject knowledge and the development of mathematical thinking skills.

The KSB framework maps naturally onto our theoretical foundations:

- Knowledge aligns with lower levels of Bloom's Taxonomy (remember, understand);
- Skills correspond to middle levels (apply, analyse);
- Behaviours represent higher levels (evaluate, create) and the transformative aspect of threshold concepts.

Thinking about the introduction of the topic in this way led to two key observations:

1. 'Algorithms' and 'algorithmic thinking' are not the same thing - one represents knowledge while the other represents a skill that must be developed through practice;
2. The development of the 'skill' aspect would be best served by embedding algorithms across the whole term rather than treating them as an isolated topic.

Students learn best, and skills develop more deeply, when presented in the context in which they are to be used (Brown, Collins and Duguid, 1989; Hallam and Ireson, 2003). This is the standpoint taken in arguing for authentic assessment (Wiggins, 1990) and is consistent with situated learning theory (Lave and Wenger, 1991).

Considering the course's immediate and ongoing aims, we produced the following learning outcomes:

1. Define and explain basic concepts and propositions in the theory of algorithms;
2. Apply algorithmic techniques to prove mathematical statements;
3. Analyse and prove properties of algorithms including correctness and complexity;
4. Employ algorithmic thinking to approach computational problems and construct proofs.

3.1. Knowledge

The knowledge students should acquire is captured in learning outcome 1: a carefully selected subset of the core concepts and theory of algorithms, presented as four fundamental questions we can ask of any algorithm:

1. Does the algorithm terminate?
2. Does the algorithm give the correct answer? If so, when?
3. How fast does the algorithm converge to the correct answer?
4. How many operations does the algorithm take?

As this is primarily a mathematics course, we deliberately limited asymptotic analysis to big-O notation, excluding other measures of complexity such as Θ and Ω. We omitted data structures and algorithm paradigms (divide-and-conquer, greedy methods, etc.) entirely, as these are covered in a more specialised 'Algorithms and Data Structures' course available in later years.

3.2. Skills

Learning outcomes 2 and 3 cover the two complementary skills identified in the design phase. The first is employing algorithms as tools to prove mathematical statements or solve problems.

Students learn to:

- Use algorithms to demonstrate existence (e.g., proving a solution exists by providing an algorithm that finds it);
- Apply algorithmic techniques to prove mathematical statements (using named algorithms to prove known properties of mathematical objects);
- Leverage algorithmic reductions to establish relationships between problems.

The second skill is correctness proofs and complexity analysis for known mathematical algorithms. We selected algorithms that arise naturally in the course's topics:

- Number theory: Euclid's algorithm and the Chinese Remainder Theorem;
- Group theory: Burnside's Lemma for counting orbits;
- Linear algebra: Basis Extension Lemma and Gram-Schmidt orthogonalisation process.

Students are introduced to loop invariants (Hoare, 1969) and their relationship to mathematical induction, seeing how inductive proofs arise when analysing recursive algorithms. For complexity analysis, they learn to prove worst-case time bounds using techniques familiar from their mathematical training.

3.3. Behaviour

Learning outcome 4 assesses students' ability to use algorithms within their toolbox of proof strategies. This is the threshold crossing: students internalise algorithmic thinking as a fundamental mathematical practice. They learn to:

- Consider algorithmic approaches when faced with existence proofs;
- Use computational thinking to structure mathematical arguments;
- Recognise patterns that suggest particular algorithmic approaches.

In doing so, they develop intuition about what makes problems computationally hard or easy, preparing them for more advanced study in both pure and applied mathematics. This behavioural

change is the transformative aspect of the threshold concept, fundamentally altering how students approach mathematical problems.

4. Example: The Euclidean Algorithm and Extended Euclidean Algorithm

The Euclidean Algorithm gives students their first exposure to a loop invariant, illustrating the threshold concept in action. Loop invariants were introduced by Hoare in his work on program correctness (Hoare, 1969; see also Floyd, 1967). Formally, a loop invariant is a property that holds before and after each iteration of a loop, serving as the inductive hypothesis in correctness proofs: by maintaining it throughout execution, we guarantee the desired outcome on termination.

This example demonstrates our scaffolding principle: students build from concrete computation to abstract reasoning through the intermediate step of algorithmic analysis.

Having been shown an example calculation of $\gcd(a, b)$, the greatest common divisor for two natural numbers a and b, students are presented with the algorithm in Figure 1.

Input: Integers a, b with $a > b > 0$
Output: $gcd(a, b)$
function GCD(a, b)
  $r \leftarrow a \bmod b$
  while $r \neq 0$ **do**
    $a \leftarrow b$
    $b \leftarrow r$
    $r \leftarrow a \bmod b$
  end while
  return b
end function

Figure 1. Algorithm presented to students for the calculation of $\gcd(a, b)$ for two natural numbers a and b

We make and prove two claims, covering learning outcomes 2 and 3:

1. The algorithm terminates;
2. The algorithm is correct.

The proof of the first claim is a standard one, invoking the well-ordering principle that is part of the axiomatisation of the natural numbers. At each iteration, b strictly decreases (since $0 \leq r < b$), and since b is a non-negative integer, it must eventually reach 0. This connects the other fundamentals of the course (axiomatisation, abstraction) with the study of algorithms.

The proof of the second claim is more interesting. This can, of course, be approached by induction. But alternatively, correctness can be proved simply by proving that the greatest common divisor is a loop invariant in this algorithm:

Theorem: Let a, b be non-negative integers such that $a > b > 0$. Then

$$gcd(a, b) = gcd(b, r) \text{ where } r = a \ (mod\ b).$$

Since students already know proof by induction, the two strategies can be compared directly: the loop-invariant proof is markedly more succinct and intuitive.

Having verified termination and correctness, students meet complexity analysis, a skill that bridges pure mathematics and computer science. We present it in stages, from intuitive observation to formal proof.

The intuitive observation is that each iteration reduces the problem size: after two iterations, at least one number has halved. This leads to the formal result:

Theorem: The Euclidean algorithm has time complexity $O(\log \min(a, b))$.

The number of iterations of the Euclidean algorithm is at most $\lfloor \log_{\varphi}(\sqrt{5} \cdot \min(a, b)) \rfloor + 1$. Since each iteration involves one division operation (which takes $O(\log a \cdot \log b)$ bit operations), the total complexity is $O(\log \min(a, b))$ iterations.

This leads naturally into the study of Bézout's Identity:

Theorem: For any positive integers a and b, there exist integers x and y such that

$$gcd(a, b) = ax + by.$$

Rather than a non-constructive existence proof, we prove this by providing an algorithm that explicitly constructs the coefficients x and y. The Extended Euclidean Algorithm maintains the same $O(\log \min(a, b))$ complexity while additionally tracking the linear combination coefficients, demonstrating that constructive proofs need not sacrifice efficiency.

5. Implementation Strategy

Having decided to embed algorithmic thinking throughout the course, we updated the syllabus as follows:

1. Reformulate mathematical arguments algorithmically. For some results we replaced non-constructive proofs with constructive ones. For example, demonstrating the Chinese Remainder Theorem through an explicit algorithm that constructs the solution rather than proving existence abstractly. For others, we replaced inductive proofs with loop invariants;
2. Create dedicated time for algorithmic study. We replaced the worked examples in the weekly 'examples lecture' with weekly 'deep-dives' into that week's main algorithm(s);
3. Provide context from the start. We introduced the motivation for and general principles of algorithms in the first lecture of term;
4. Formalise the theory at the appropriate point. In the final lecture of term we treated algorithms formally (definitions, abstraction, and results on asymptotic analysis) only once their full context had been established.

6. Transferability

Although this intervention was developed for a cohort with strong incoming mathematical preparation, we believe its core design transfers to settings where students are less mathematically proficient, and may even suit them better. It is worth separating the portable elements from the local conditions that enabled them. The portable elements are the KSB framing, the distinction between knowing algorithms and thinking algorithmically, the four organising questions, embedding algorithmic thinking throughout rather than in isolation, and using constructive proofs as scaffolding toward abstract reasoning.

For such a cohort, the constructive route is arguably an advantage rather than an obstacle. Building an object explicitly offers a concrete foothold before the leap to non-constructive abstraction,

consistent with the ZPD scaffolding described above. Adapting the approach would likely involve slower pacing, lightening or omitting the formal final-lecture treatment of asymptotic analysis, choosing gentler exemplar algorithms and proofs, and adjusting assessment accordingly. A direct evaluation in such a setting would be a valuable next step.

7. Conclusion

By adopting a KSB framework and integrating algorithmic approaches throughout the curriculum, we have created a course that maintains mathematical rigour while developing the computational thinking skills essential for modern graduates.

While formal evaluation is planned for the next academic year, the 2024/25 delivery was a first implementation rather than a study designed to gather data, and we report no systematic findings here. Course feedback forms drew too few responses to support meaningful analysis. We can offer only the informal observation that students engaged readily with the material, and several voluntarily explored and implemented the algorithms beyond what was required — but we present this as an impression to be tested, not as evidence.

The intervention shows that pure mathematics courses can incorporate algorithmic thinking while keeping their essential character, giving students additional tools for mathematical reasoning and preparing them for the increasingly algorithmic nature of academic research and professional practice.

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CASE STUDY

Using Annotation Sheets to Teach Undergraduates to Learn Proofs and Derivations

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Abstract

On arrival at university, undergraduate mathematics students often struggle to take effective notes in lectures, particularly when they are learning content which requires a high level of understanding, such as proofs and derivations. Annotation sheets, which contain the algebraic steps of proofs or derivations with spaces left for students to add explanations, can provide a structure for taking notes which allows students to focus on the reasons behind the steps. These sheets have been introduced into two applied maths modules and initial observations suggest that they have a positive impact on students' note-taking and mathematical learning.

Keywords: Note-taking, notes, proof, understanding, transition.

1. Introduction

When mathematics undergraduates arrive at university, their approach to note-taking is often very simplistic. As described by Freitag (2020), many students attempt to record verbatim anything that their lecturers write down or display in a written format. This means that students have a complete record of the content they have been taught, which they can then refer back to later. It also encourages them to engage, to a certain extent, in the lecture as they must be continually reading and copying. However, students are often so busy copying what their lecturer is writing, that they do not listen to what the lecturer is saying. These spoken comments can be very important for understanding the written content (Lew et al., 2016) but students who are too focused on copying down written information often overlook them (Fukawa-Connelly et al., 2017).

This is particularly problematic when students are learning ideas which they need to understand rather than just memorise, such as proofs or, in more applied modules, derivations (which I define as procedures using logical steps to produce a given equation or formula from a set of assumptions or known statements). In the case of either proofs or derivations, students often write down the algebraic lines of working, which they might consider to be the "final answer" to a question, without making any note of the explanations for why each step might be expected to follow from the previous one or lead to the desired final result (Lew et al., 2016). Such notes are ineffective for students trying to understand the content later, as they do not contain the key information which aids understanding.

This inability of incoming undergraduates to take effective notes on proofs and derivations is perhaps unsurprising, as school-level mathematics in the UK is far more focussed on mathematical procedures which can be practised and memorised without being fully understood (Darlington, 2014). Although A-Level (pre-university) mathematics examinations do assess students' ability to "construct extended arguments and proofs" (Joint Council for Qualifications, 2021), these skills constitute a small part of the course and are rarely mastered by students achieving modest (B-C) grades. Students therefore often transition to university with little experience of learning proofs and derivations and subsequently find these aspects of their course challenging (Laugwitz et al., 2025; Iannone & Miller, 2019).

In an attempt to address these problems and help students to learn proofs and derivations effectively, some lecturers use partial lecture notes (otherwise known as gappy, guided or skeletal notes). These

notes contain a significant part of the content with strategically placed gaps to be filled in by the student. This gives students time to listen to the lecturer, as they do not always have to be copying down information, whilst also requiring them to pay attention so as to fill in the gaps. There is evidence that partial lecture notes can improve students' understanding during lectures (Feudel & Panse, 2022) and their subsequent academic performance (Cardetti et al., 2010), although this may not always be the case (Machida et al. 2018). Regardless of this, however, the vast majority of students still end up with identical notes either provided by or copied directly from the lecturer (Feudel & Panse, 2022; Iannone & Miller, 2019). This is considered to be a disadvantage by some students who prefer to organise their notes in their own way (Feudel & Panse, 2022) but it also poses the problem that students are not developing note-taking skills whilst at university.

The ability to take notes is a valuable skill for graduates in any profession (BPM Team, 2025; Indeed Editorial Team, 2025), as they will often be required to identify the most important points from a large quantity of written or verbal information and summarise these points succinctly in a format which will be useful for them later on. This applies to numerate careers as much as any others (ACCA, 2025; Ban, 2024) and so it is highly beneficial for mathematics undergraduates to improve their note-taking whilst at university. This is not generally achieved by using partial lecture notes, as students take very few notes and these are usually stipulated by the lecturer, nor is it achieved if students simply copy verbatim from the board.

Overall, it would be ideal to provide a structure whereby students actively learn to take notes which include the reasons behind the steps of proofs and derivations, as well as the algebraic steps and formal statements. These notes would be personal to the student, containing whatever information they needed to understand the content and revise it later. In this article, I introduce a method of note-taking for proofs and derivations with the aim of achieving these goals.

2. Implementation

To support undergraduate mathematics students with notetaking, so-called annotation sheets were introduced into a first-year Classical Mechanics module and a second-year Vibrations & Waves module. Annotation sheets are hand-out-style documents which contain the key algebraic lines of a derivation or proof with appropriately sized gaps for students to write their own notes between the lines. These notes are individual to the student, unlike in many types of partial lecture notes where there is a correct answer which goes in each space (Feudel & Panse, 2022). The students were provided with annotation sheets during lectures and were encouraged to write down whatever they thought would help them to understand or revise the derivation when they looked at it again later.

Some examples of annotation sheets are shown in figure 1. Figure 1A is an annotation sheet used in first-year Classical Mechanics for the derivation of the work-energy principle. Figure 1B shows an example annotation sheet which could be used in a foundational analysis module for the proof of the limit of a sum.

Annotation sheets can be used flexibly, depending on the context in which they are used. For example, in the small-cohort module, the sheets were printed out and provided to the students at the start of each lecture, whereas in the large-cohort module, digital versions of the sheets were provided to the students in advance of each lecture. Students could then choose either to print the sheets for themselves or to annotate them digitally.

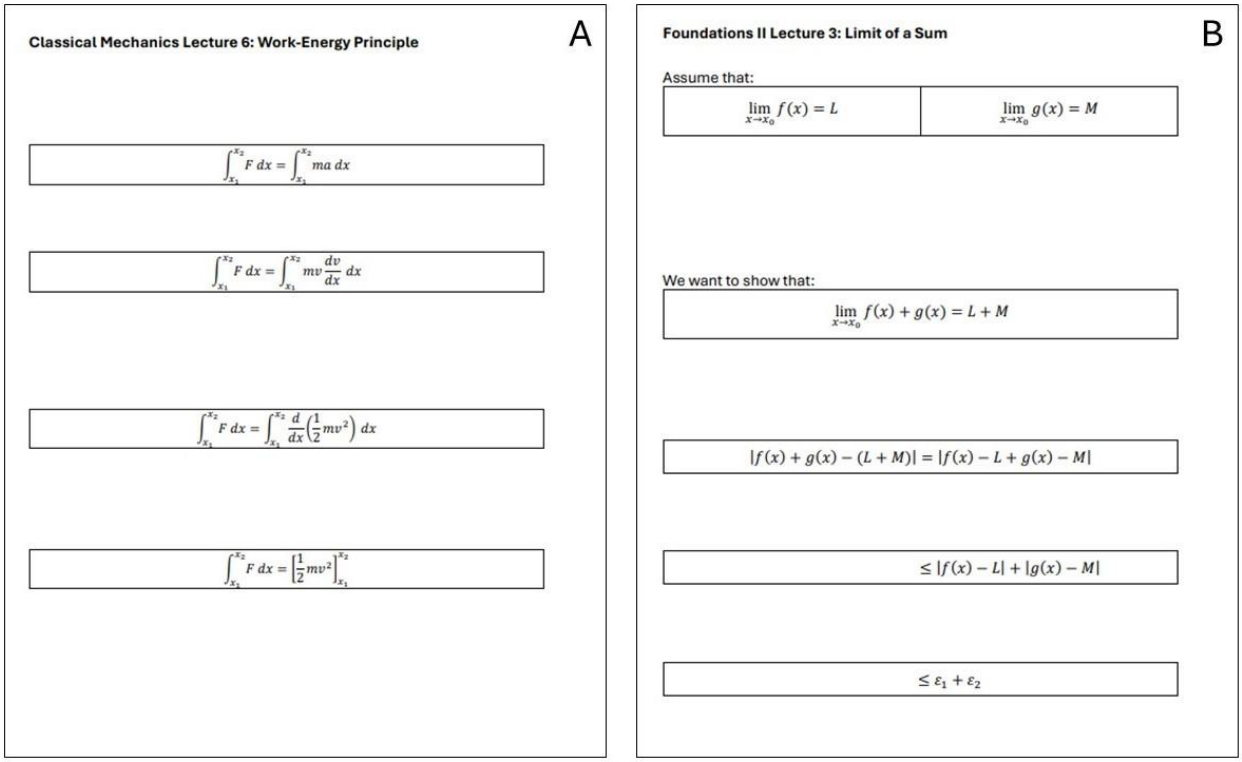


Figure 1. Examples of blank annotation sheets.

Annotation sheets are also very flexible in terms of their content. The lecturer can leave gaps for the students to write down any notes, explanations or lines of working which they think the students will benefit from copying out or writing in their own words. For example, in the sheet for the proof of the limit of a sum (figure 1B), spaces have been left for students to write out the definition of a limit, as well as to make more personalised notes about how the steps follow from one another. This ensures that the students will write out this definition plenty of times, helping them to memorise it.

The annotation sheets were also used to teach the students how to take notes by reducing the scaffolding provided over the course of the semester. At the start of each module, the lecturer showed the students an example of how to fill in the sheet by adding notes to their own sheet under a visualiser. The lecturer thereby provided the students with examples of how they could annotate their sheets, whilst also encouraging them to personalise their notes and only include the content which they found helpful. Over the course of the module, the lecturer provided less guidance on what notes should be included. By the end of the semester, the lecturer explained the derivations verbally whilst making less-structured notes on the board and then gave the students time to formulate their own notes and add them to their sheets. The length of time required by the students varied depending on the length and nature of the derivation but, as students often took some notes whilst the lecturer was talking, it was not generally longer than a couple of minutes.

Figure 2 shows some examples of how the annotation sheet for the work-energy principle could be completed. The notes in figure 2A are relatively sparse. The student has used the abbreviation “N2” for Newton’s second law to justify the first line of working. They have then stated a key formula which is needed to get to the second line and included the method used to show that the second and third lines are equivalent. Finally, they have interpreted the meaning of the terms in the final equation. The notes in figure 2B, on the other hand, are much more detailed. Among other things, they contain a reference back to a previous derivation from lecture 2, a more detailed explanation of the use of the chain rule and an explicit statement that the last line describes the work-energy principle. Both

of these sets of notes are equally valid, as long as they contain the information that these individual students need to understand the derivation.

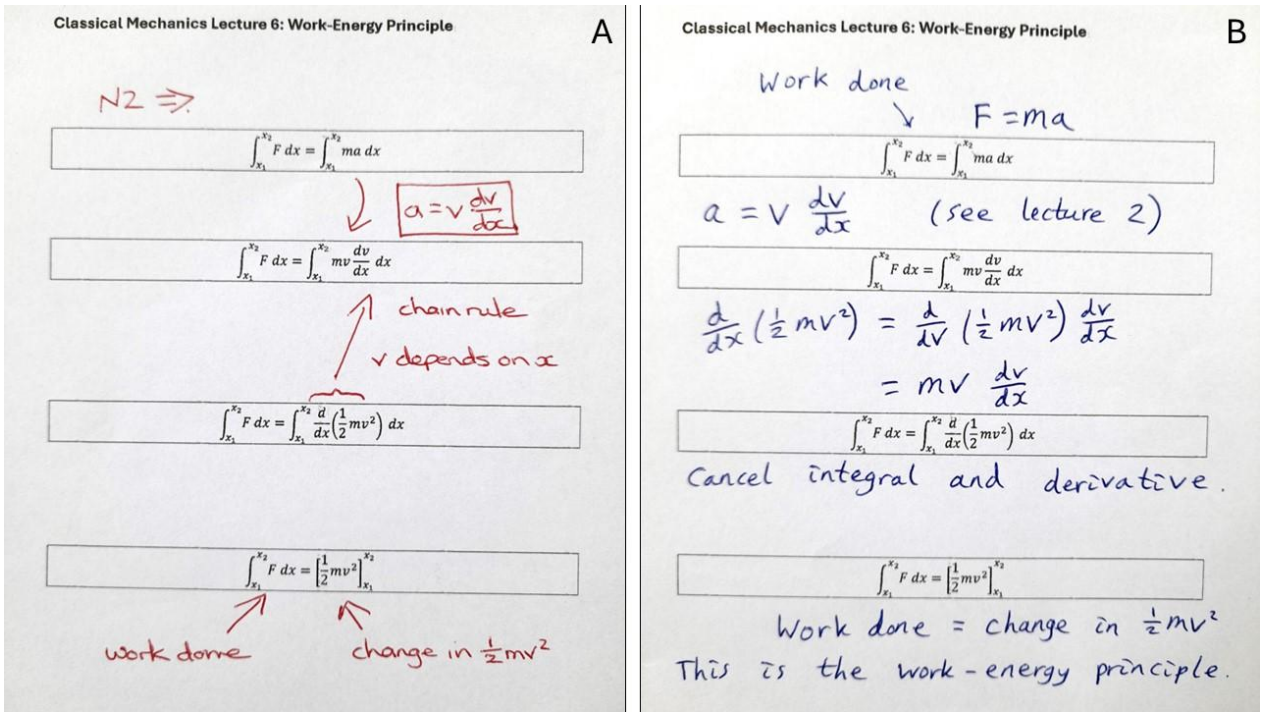


Figure 2. Examples of completed annotation sheets.

To ensure the accessibility of the annotation sheets, a number of different formats were made available to students. All sheets were provided digitally, well in advance of the lectures, in both PDF and Microsoft Word formats. The printed sheets were provided in different background colours for students with visual stress and large-print copies were available on request. Moreover, students were not required to use the sheets if they preferred to take notes in a different way. The lectures were also recorded, allowing any students who could not attend to add their annotations at a later stage. This was important as the module lecture notes contained only the steps from the annotation sheets, without any explanation, to prevent students from copying all of their annotations from the lecture notes.

3. Feedback & Observations

Student feedback on the annotation sheets was extremely positive. When asked, “What has worked well on your module?” in the end-of-module feedback survey, many students mentioned the annotation sheets. In particular, they commented on how the sheets provided structure to the derivations, thereby making them easier to follow in the lectures. The students also said that the sheets provided a more manageable way to learn derivations, as they were broken down into smaller steps. A couple of students on the smaller-cohort module mentioned the benefits of having the sheets printed.

One student also described how they used the sheets for revision. They reported that they practised filling in the gaps on the sheets, then removed the sheets and derived the algebraic lines of working using their understanding of the steps. Another student explained that the sheets had helped them to learn how to take notes in lectures. They reported that they had previously copied down everything

their lecturers wrote on the board, but the sheets gave them the confidence to make more personalised notes for other modules, for instance by annotating their lecture notes.

The students' notetaking abilities in the modules which used the annotation sheets also appeared to improve over time, both when using the sheets and making notes on other aspects of the module. As the semester progressed and the lecturer provided less instruction on how to complete the sheets, the students were noticeably more attentive to what the lecturer was saying and began to take more individualised notes. Some students who had initially copied down everything that was written on the board clearly became more considered in their notetaking, as they began to be selective about what they copied, included additional information in their notes and rephrased content in ways that made sense to them.

The annotation sheets may also have helped to improve students' academic outcomes. Most students scored well on the derivations-based questions in their assessments following the introduction of the annotation sheets and, in revision sessions, students were generally confident in explaining the steps of the derivations, something which previous cohorts of students had struggled with. The annotation sheets also have benefits for the lecturer. They are quick and easy to make, particularly if the derivations or proofs already exist in a digital format (for instance, in the lecture notes). The algebraic steps can simply be copied from the original document into a blank annotation sheet, and appropriately sized spaces added between the lines.

The structure of the sheets also provided an alternative type of exam question. Students were given the algebraic steps of a derivation and were asked to explain how particular lines followed from the preceding lines. This had several benefits over asking students to reproduce the full derivation. Firstly, these questions were much quicker for students to answer, allowing time for more content from the module to be assessed. Secondly, these questions forced students to demonstrate their understanding and so prevented them from obtaining marks simply by memorising algebra with no understanding whatsoever. Finally, the structure of the questions supported students who were struggling; even if they could not remember the beginning of the derivation, they could still show their understanding of later parts. The steps which students were asked to explain in these questions had to be chosen carefully to ensure fair and transparent marking. In particular, steps which rely on one key idea, assumption or formula work well, as any correct explanation of this idea can then be awarded the marks.

The annotation sheets also saved time in lectures, compared with having to allow students the time to copy everything from the board. As well as this, they allowed more flexibility than having to stick rigidly to the structure of partial lecture notes. Of course, time still needed to be set aside during lectures to teach the students how to use the sheets and to allow them to construct their notes. This was potentially more time-consuming than traditional approaches at the start of the module, when the sheets were unfamiliar to the students and their note-taking skills were limited. However, once the students got used to using the sheets, their notetaking became quicker.

Another potential problem is the financial cost and environmental impact of printing the sheets. This can, of course, be mitigated against by providing the sheets digitally. This worked well in the large-cohort module, especially as each sheet was labelled with the lecture in which it would be used, allowing students to prepare their sheets beforehand. Many of the students had tablets which allowed them to annotate PDF versions of the sheets. Others typed their notes into Word document versions, or else printed the sheets themselves and annotated them by hand. However, this does potentially cause a problem for students who lack the necessary technology to annotate sheets digitally or the funds to print their own hard copies.

4. Discussion

By providing a structure for students to take their own notes, annotation sheets can improve students' general note-taking skills and support them to understand the steps of proofs and derivations. They provide a middle ground between traditional chalk-and-talk lectures and lectures based on partial lecture notes, allowing lecturers to provide some material in a more flexible and spontaneous way and yet removing the need for students to copy down large quantities of algebra whilst the lecturer gives valuable oral explanations. Using these sheets, the lecturer can actively encourage students to develop their note-taking skills, rather than removing the need for them to take notes or expecting them to learn this skill on their own.

Annotation sheets are a good way for students to learn and revise proofs and derivations, as they encourage students to focus on the reasons behind the steps, rather than just the algebra and technical wording which constitutes the final derivation or proof. This is highly beneficial for the students' deeper understanding of the content and, by learning the reasons rather than rote-learning the algebra, it provides a much quicker and easier method for learning proofs and derivations in preparation for an exam, which is strongly recommended by lecturers (Houston, 2009; Alcock, 2012). The sheets also enable the lecturer to focus on the explanations more heavily themselves, as they are not spending all of their time writing algebra on the board, which in turn emphasises the importance of understanding the steps to the students.

The purposes of annotation sheets may be best met when they are used with first-year or foundation-year students as they transition to university. At this stage, many students have little experience of note-taking other than the expectation for them to copy verbatim from the board at school (Squelch, 2015). They are also unfamiliar with learning proofs and derivations and may only ever have learned mathematics by practising procedures or memorising methods. By using annotation sheets with new students, they may be prevented from developing unhelpful habits when learning proofs and derivations, such as trying to memorise the algebraic steps without understanding them. Hopefully, they will then be able to develop sufficient note-taking skills as to be able to take notes independently in the latter stages of their course.

Annotation sheets, or some variation on them, may also be useful in disciplines other than mathematics. Undergraduates in chemistry and economics are reported to struggle with note-taking (Bucat & Williams, 1989; Artz et al., 2022) and even students studying English, history and psychology need to develop their note-taking skills at university (Baker & Lombardi, 1985; Locke, 1977). An annotation sheet essentially contains the formal steps of an argument, with spaces for explanations of these steps to be added, and this principle could be applied to a wide variety of subject areas.

In the mathematical sciences, annotation sheets could also be used in Maths Support settings, as well as in formal lectures. Proofs and derivations are common areas of difficulty for undergraduates (Laugwitz et al., 2025) and so are frequently the cause of enquiries in Maths Support. To help with this, a set of blank and completed annotation sheets could be created for those proofs and derivations which are most often poorly understood. These would not necessarily help with note-taking but could still fulfil their purpose of structuring proofs and derivations and encouraging students to focus on the reasons behind the steps.

Annotation sheets could also be beneficial for learning mathematics beyond just proofs and derivations. For example, undergraduate mathematicians are often taught procedures which they are expected to understand as well as be able to implement. Students often focus on memorising how to carry out the procedure (MacBean, 2011) but giving them these steps on an annotation sheet

and encouraging them to add the reasons behind the steps could highlight the importance of deeper understanding.

Going forward, it would be beneficial to trial the annotation sheets in a wider range of modules. Thus far, they have only been used to teach derivations in the applied maths modules which the researcher was delivering at the time, and so it is important to find out whether or not they work equally well in teaching proofs in pure maths modules. Data should also be collected on the effectiveness of annotation sheets for students' note-taking skills and understanding of mathematical proofs and derivations. A more formal survey of students' perspectives might also clarify how students use the sheets and in what ways they find them helpful.

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CASE STUDY

Deeper Discussions: Discussion Based Tasks for Developing Problem-Solving and Critical-Thinking Skills

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Abstract

Problem-solving and, more generally, critical thinking are key components of being a mathematician and some of the most desirable skills for employers of STEM graduates. This article presents a novel learning activity, called Deeper Discussions, for developing such skills within mathematics education. The strategy revolves around discussion activities where students tackle problems that are often ill-formed or open. By leveraging pedagogic theories such as situated learning, dialogic teaching and problem-based learning, classroom dialogue is used as a mechanism for modelling these cognitive skills and enabling students to practise those skills. In this article, we present a detailed outline of these activities, the motivation behind them and their pedagogical underpinnings. We conclude the article by discussing considerations for this method moving forward.

Keywords: Problem-solving, critical thinking, problem-based learning, situated-learning, sociocultural learning, dialogic teaching, Socratic questioning, interleaving.

1. Introduction

Problem-solving is an integral part of being a mathematician. In fact, Halmos claimed that,

"*The mathematician's main reason for existence is to solve problems, and that, therefore, what mathematics really consists of is problems and solutions*" (Halmos, 1980).

Moreover, problem-solving is one of the most sought-after skills from STEM graduates (Holik, 2023, McGunagle and Zizka, 2020). Hence, the development of problem-solving and, more generally, critical thinking skills needs to be put at the heart of mathematics education. The traditional lecture would seem not to be the best for achieving this (Klegeris et al., 2017). However, it can be difficult to move away from this mode of delivery given the linear nature of mathematics, where subsequent ideas need previous concepts to be firmly grasped. This raises a question of how we can embed critical thinking into a standard mathematics unit in a way that is pedagogically sound and that genuinely represents how mathematicians approach their work.

In this article, we present a learning activity that addresses this problem by putting the development of higher-order thinking skills at the heart of learning. The activity, called a *Deeper Discussion* (DD), involves asking students to tackle broad and often ill-defined problems, primarily in tutorials in small groups. Then, using well-established pedagogies such as dialogic teaching, situated learning and problem-based learning, classroom discourse is leveraged to model problem-solving skills and to give students opportunities to engage with those skills. Moreover, with the answers to these problems providing a basis for concepts introduced later in the course, DDs form an integral part of the learning in the courses where they are used.

We start in section 2 with a general description of the strategy, followed by an explanation of the pedagogical frameworks that underpin the method. We then proceed to give a detailed explanation of how the tutorial discussions for these DDs are delivered. Lastly, we have a very brief discussion about future plans for DDs.

2. What are DDs?

2.1. A general description

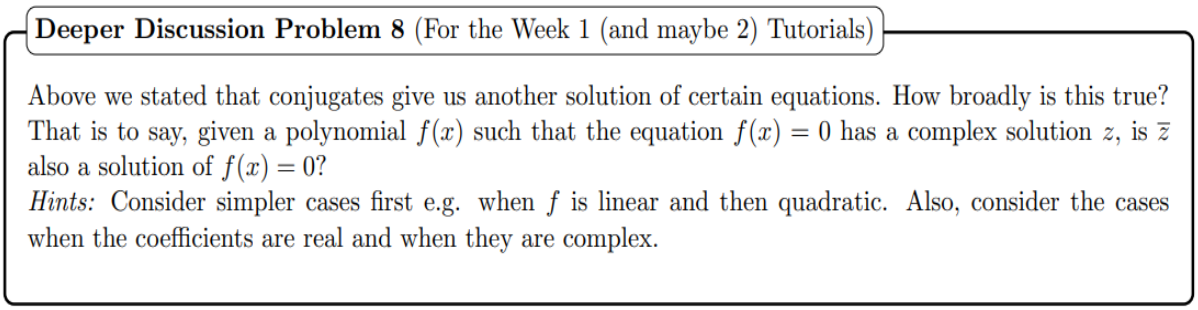
The general strategy for the DDs is as follows:

1. The problems are shared with students before tutorials in either lecture notes or exercise sheets for students to consider in their own time.
2. The problem is then discussed in tutorials. This discussion has the following three phases
   - **Phase 1:** A class discussion of the problem, where the problem is recapped, set in context and possibly analysed.
   - **Phase 2:** Students attack the problem in a small group of about two or three students.
   - **Phase 3:** A class discussion where ideas are brought together to form response to the problem. This response may be an answer to the problem or a reformulation of the problem. In the case of the latter, the class returns to phase 2 and, hence, this process is often cyclical.
3. The answer attained is often revisited in later lectures as a basis for learning further content.

Note that in what follows, we will refer to the person leading the tutorial as the "tutor".

2.2. Theoretical Bases of the Approach

Since the main purpose of DDs is to develop certain skills, an apprenticeship approach has been adopted for these tasks. In particular, the construction and delivery of DDs aligns with Lave and Wenger's (1991) *Situated Learning* (SL) model of learning, which views learners as apprentice members of what they call *communities of practice*, who are attempting to become full members. DDs have most of the core qualities of SL. For instance, DD tasks offer *authentic practice*, which is key to SL. Authentic practice is the use of learning tasks that reflect the practise of the professionals in the given community of practice. As such, the tasks elicit authentic skills. To reflect this, DD problems are intended to authentically represent the *kind* of problem that mathematicians consider. Figure 1 below presents an example of such a problem.



Deeper Discussion Problem 8 (For the Week 1 (and maybe 2) Tutorials)

Above we stated that conjugates give us another solution of certain equations. How broadly is this true? That is to say, given a polynomial $f(x)$ such that the equation $f(x) = 0$ has a complex solution z, is $\overline{z}$ also a solution of $f(x) = 0$?

Hints: Consider simpler cases first e.g. when f is linear and then quadratic. Also, consider the cases when the coefficients are real and when they are complex.

Figure 1. An example of a Deeper Discussion problem on a Foundation Year mathematics unit, MATH19812 at the University of Manchester.

While almost all mathematicians would consider the problem in Figure 1 as "answered" now, it draws upon themes, such as the solvability of equations and the structure of number systems, that are of profound interest to mathematicians and have been so for millennia.

Moreover, this problem authentically represents mathematical inquiry in style as well as in content. Mathematicians generally ask overarching and ill-defined questions which they then reduce to exact formal ones. This is reflected in DD 8 above (figure 1) where the notion of "polynomial" is ill-defined. More precisely, the coefficients are not specified. The problem requires the students to identify this

ambiguity and then critically consider possible options. Notice that there are various legitimate choices here, and the answer changes with different choices for these coefficients. Thus, these problems call upon students to use critical thinking skills which are generally not required in traditional mathematics problems which tend to be closed and exact.

Further to the authenticity of these problems, their answers serve as motivation and a theoretical foundation for latter content. This reflects the fact that in mathematics, new concepts arise out of tackling (general) problems such as these. This also fits into the *Problem-Based Learning* framework, which has been shown to improve problem-solving and critical thinking skills in mathematics (Aba-Oli et al., 2025). On a course level, this is also using the *interleaving* technique, which can also help students apprehend mathematical concepts (Rohrer et al., 2015).

Learning as Social Participation is another core component of SL. This is the idea that knowledge is co-constructed through social interaction within the given community of practice when engaged in an authentic task. This is based on Vygotsky's (1978) idea of *sociocultural learning*. Learning in DDs is almost entirely dependent on social interaction in the form of discourse. The choice of using dialogue in this way is heavily influenced by the ideas of Vygotsky (1962) and, especially, Sfard (2008), who conceptualise certain kinds of thought as a form of communication. Under this framework, the problem-solving process can be viewed as a form of dialogue, be it internal or external. As such, classroom discourse becomes a modality for modelling and practising such thinking processes.

To practically achieve this in the classroom, DD delivery leans heavily into *Dialogic Teaching* strategies (Alexander, 2020). This is a pedagogical approach that emphasises the use of classroom dialogue to "engage interest, stimulate thinking, advance understanding, expand ideas, and build and evaluate arguments, empowering students for lifelong learning and democratic engagement" (Alexander, 2025). In particular, the method of *Socratic Questioning* is extensively used in the delivery of DDs. This is a questioning strategy, dating back to Socrates, where an idea is interrogated by a series of questions that reduce it to the fundamental principles it is built on (Paul and Elder, 2007). Clearly, this lends itself very well to a logically deductive practise such as mathematics. It allows the tutor to map their own thinking process towards a solution with a series of questions. Moreover, it offers a powerful tool for incorporating students into this dialogue. Using it this way, the tutor does not simply take students' answers but, rather, probes them with further questioning, e.g. asking why they think that. This not only clarifies the students' understanding to the tutor but also trains the student to interrogate and evaluate their own thoughts with the questions the tutor poses.

Using Bloom's (Anderson and Bloom, 2014, Bloom, 1956) taxonomy can also prove to be very useful for planning and executing questioning strategies. By ascertaining the students' current understanding, the taxonomy allows us to determine the types of questions that may be most effective for helping students make progress with the problem. Such questioning not only highlights refinements to their ideas, but also to the students' own questioning process. Hence, such a questioning strategy is also a feedback mechanism, pointing out to students how they might develop their critical thinking skills.

DDs also touch upon *Legitimate Peripheral Participation*, which is another facet of SL. This is the idea that new members of a community of practice start at the periphery of the community and gradually move further inwards through authentic participation. As mentioned earlier, DD problems are intended to represent questions that are of genuine and deep interest to the mathematical community. By taking on authentic tasks, students are required to act as novice mathematicians, and hence, it is hoped that students will come to believe that they are mathematicians. Moreover, the authenticity of the problems conveys cultural perspectives of the mathematical community, something that can be consolidated by the discussions in tutorials with the tutor relaying *why* this

problem is important to mathematics. This allows students to adopt these cultural perspectives, should they wish to.

2.3. Delivery of DD discussions in Tutorials

The desired critical thinking skills are primarily developed in the tutorials for these DDs. As such, this section expands on the delivery and structure of the tutorials. In particular, we give more details on how the pedagogic strategies mentioned in the previous section are implemented.

2.3.1. Phase 1: Pre-Discussion

The main purpose of this phase is to recap the problem and set this problem in the context of the course. This is important for underscoring the authenticity of the problem. Each DD problem arises naturally while studying related ideas on the course. For example, DD 8 in Figure 1 appears when first encountering complex conjugates. Conjugates are introduced after observing that solutions of certain polynomial equations are conjugate pairs. DD 8 is then posed to explore to what extent is this true. While this would be stated in lectures, the tutor is asked to reinforce this in phase 1 of the tutorial.

While recapping the problem it is natural to review key terms e.g. complex conjugates. However, the ill-defined nature of DDs makes this a richer process and offers choices regarding to what extent the tutor unpacks the ill-defined terms at this stage. For instance, with DD 8, the tutor can choose to define that a polynomial as an expression of the form $a_n x^n + a_{n-1}x^{n-1} + \cdots + a_0$, where $a_n, \ldots, a_0$ are simply stated to be *numbers*. This connects the students to their prior knowledge of the word "polynomial", but at the same time, it gives them an opportunity to practise critical thinking in phase 2 by identifying the ambiguity in the word "number" and then considering how it can be interpreted here. The ambiguity can then be brought to the fore in phase 3 (see section 2.2.3. below).

While this phase is led by the tutor from the front, student participation is integral for not only engagement but also to enjoin students in the critical thinking process. The tutor is asked to do this using the questioning strategies mentioned in the previous section.

2.3.2. Phase 2: Small Group Discussions

This is the main opportunity for the students to practise the desired cognitive skills. The questioning in the first phase would allow those asked to practise the desired thinking skills in an impactful way. However, this phase offers a much more accessible and direct opportunity for all students to participate in the discourse, and therefore to practise those skills.

As with all apprenticeship models of learning, it is important for the tutor to still provide guidance at this stage. For this reason, the tutor must circulate and talk with the groups. However, in these scenarios the role of the tutor is not to provide answers. Instead, it is to elucidate the students' understanding and how it can be developed using questions informed by the Socratic method and Bloom's taxonomy. For example, the tutor may ask,

- *Why do you think that?*
- *In what context is that true?*
- *What if we change X to Y?*

This also provides very direct feedback, offering a refinement of the questioning used in that specific group.

2.3.3. Phase 3: Synthesising and Evaluating Ideas

In this phase, ideas that students have developed in phase 2 are brought together in a class discussion with a view to providing a response to the question. This response might be a direct answer, but it can also be a reformulation of the question or a mixture of the two. The *cumulative* feature of dialogic teaching (Alexander, 2020) is very prominent in this phase and is important for accessing higher-order thinking skills such as analysing, evaluation and creativity (Anderson and Bloom, 2014). The tutor not only models these skills here but also makes the students participants of the thought process by carefully piecing together different ideas shared by students in phase 2 to form response to the problem. For example, when tackling DD 8 above, it is likely that most groups will assume the coefficients of the polynomials are real numbers, but some may notice that the question allows for complex coefficients. If so, the tutor can ask one of each type of group to share how they started to address the problem in this phase. In doing so, they can point out that the problem breaks down into two sub-problems, one where the coefficients are restricted to the real numbers and the other when the coefficients are permitted to be complex. Moreover, if the tutor had identified groups that made progress in any of these sub-cases, they can ask such groups what they attempted at this stage. Alternatively, the tutor can now return to phase 2 and ask the students to consider one or both sub-cases in their groups without attempting to solve them now. This would enable the entire class to consider these more precise questions, which many may not have done yet if they had not derived the questions previously.

By using students' ideas to build the response, the students are given greater ownership of the development of concepts on the course, which in turn creates a form of legitimate peripheral participation.

3. Discussion: Going forward

Having developed the strategy, it would seem appropriate to now measure the impact of DD tasks. While feedback from students has been obtained, this was primarily for professional and course development purposes. Hence, the immediate next steps would be to obtain research-standard student feedback on their perception of the impact of these activities on their critical-thinking skills and understanding of concepts.

To follow on from this, it would also be valuable to obtain a more objective measure of the impact that the strategy has on students' problem-solving and critical thinking skills. This could potentially be done using pre- and post-assessments of their critical thinking skills. Moreover, the MicroDYN approach developed by Greiff et al. (2012), may offer a way to develop an assessment instrument for these purposes. However, a thorough study of this method would need to be done to ascertain whether this is the case and, if so, how.

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RESEARCH ARTICLE

Career and portfolio development in data science apprentices

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Abstract

Traditional mathematics programmes have often emphasised subject knowledge over employability and soft skills, despite growing recognition from employers and professional bodies of the importance of these competencies, especially considering rapid workplace changes driven by AI. This paper explores the use of authentic assessment to support such skills through real-world tasks, focusing on a teaching block within the Data Scientist Degree Apprenticeship at the University of Nottingham. Designed to prepare final-year apprentices for their careers and the End Point Assessment (EPA), the block emphasised skills development, portfolio building, and readiness for a professional discussion. Survey data from two cohorts revealed that while the teaching block was positively received initially, confidence in EPA preparedness declined over time, particularly among apprentices earlier in their careers. These findings suggest a need for sustained support and have broader implications for embedding employability-focused, authentic assessment strategies in both degree apprenticeships and traditional mathematics curricula.

Keywords: Apprenticeships, assessment, portfolio, employability skills.

1. Introduction

Employers and professional bodies increasingly highlight gaps in graduates' employability and soft skills, particularly in STEM subjects were rapid technological change demands adaptability. In mathematics, the Institute of Mathematics and its Applications (IMA) emphasises the need for transferable skills such as teamwork, self-management, and communication (IMA, 2021)

This study focuses on career development within the Level 6 Data Scientist Degree Apprenticeship at the University of Nottingham. Unlike traditional undergraduates, apprentices are working in a workplace and studying for 20% of their time over 3.5 years in a hybrid fashion. Their final assessment, the End Point Assessment (EPA), requires them to demonstrate knowledge, skills and behaviours through a knowledge test, a work-based project report, and a professional discussion informed by a portfolio of six-eight workplace evidence.

To support EPA and career readiness post-apprenticeship, the university developed a bespoke six-week teaching block, 'Becoming a Professional Data Scientist', delivered in the third year. It combines weekly online activities (interactive slides, guest speakers from data science, and applied activities such as CV writing) with an in-person block halfway through the teaching block featuring an in-person guest speaker, mock professional discussion and a CV feedback exercise. The teaching block commenced in September 2023, with the second cohort starting in September 2024.

Prior to completing the portfolio in year 3, apprentices undertake authentic assessments in prior years of the apprenticeship, which can be later used in the portfolio as an evidence piece. In the context of the Data Scientist Degree Apprenticeship, we define authentic assessments to be assessments that use work data to solve a work problem.

Degree apprenticeships remain underrepresented in UK higher education with only 13.9% of new apprentices in England enrolled at degree level in 2022/23 (Bolton & Lewis, 2024). Limited literature

exists on career and portfolio development in this context, and the upcoming apprenticeship levy cut (Chowen, 2025) may further impact uptake of degree apprenticeships.

This study evaluates the impact of the teaching block on EPA and career preparedness, addressing three research questions:

1. To what extent did the dedicated teaching block influence apprentices' perceived preparedness for the EPA?
2. How did the teaching block contribute to apprentices' sense of preparedness for their future careers as data scientists?
3. Is there a difference between the two cohorts in terms of perceived preparedness for the EPA and future careers?

2. Rationale and relevant literature

Employers report that graduates lack key soft skills such as communication, collaboration, critical thinking and building relationships, and that these skills are increasingly critical for success in the workplace (Robinson, 2024; Succi & Canovi, 2020). This has been highlighted as a particular issue in STEM disciplines, where rapid changes in technology can render some knowledge and skills obsolete within a few years (Smith & White, 2019). As a result, Universities need to provide courses that foster adaptability and professional competencies.

The recent rise of generative AI has further shifted employers' expectations of graduates, placing greater emphasis on soft skills, over traditional knowledge (Walker, 2024). For degree apprenticeships these skills are especially important, as they must demonstrate both subject knowledge and workplace behaviours and skills through the EPA. Authentic assessment – using real-world tasks to develop and evidence skills – offers a valuable approach to bridging this gap (Symonds & Mott, 2024).

To address these needs, we designed a dedicated teaching block within the Data Scientist Degree Apprenticeship which aligns with broader calls to embed employability and soft skills development within mathematics curricula, including traditional undergraduate programmes (Institute of Mathematics and its Applications, 2021).

3. Methodology

The study evaluates the impact of the 'Becoming a Professional Data Scientist' teaching block on apprentices' preparedness for the EPA and their post-apprenticeship careers and addresses the three research questions that are defined in the Introduction.

3.1. Survey analysis

Four surveys were sent to all apprentices enrolled on the programme.

- Cohort 1 (started 2021/22): Surveyed in November 2023 and July 2024, with response rates of 37.5% (6/16) and 81.3% (13/16);
- Cohort 2 (started 2022/23): Surveyed in November 2024 and July 2025, with response rates of 58.3% (7/12) and 75% (9/12).

Each survey used Likert-scale questions and apprentices were encouraged to give reasons for their responses. Respondents were also encouraged to give any other constructive comments regarding the preparation for the EPA and future careers. Quantitative results were analysed graphically. Due to the small cohort size, findings are not statistically significant.

4. Results

Four surveys were conducted across two cohorts of apprentices (Cohort 1: 2021/22 start; Cohort 2: 2022/23 start) at two time points: immediately after the conclusion of the third-year teaching block (November) and approximately eight months later (July). Response rates ranged from 37.5% to 81.3%. Cohort 1 primarily comprised experienced professionals, while Cohort 2 was mainly made up of recent school leavers.

4.1. To what extent did the dedicated teaching block influence apprentices' perceived preparedness for the EPA?

Survey responses indicated that the teaching block was positively received, with 100% of respondents initially agreeing it supported their EPA preparedness (Figure 1). Confidence declined slightly by July, particularly among less experienced apprentices in Cohort 2.

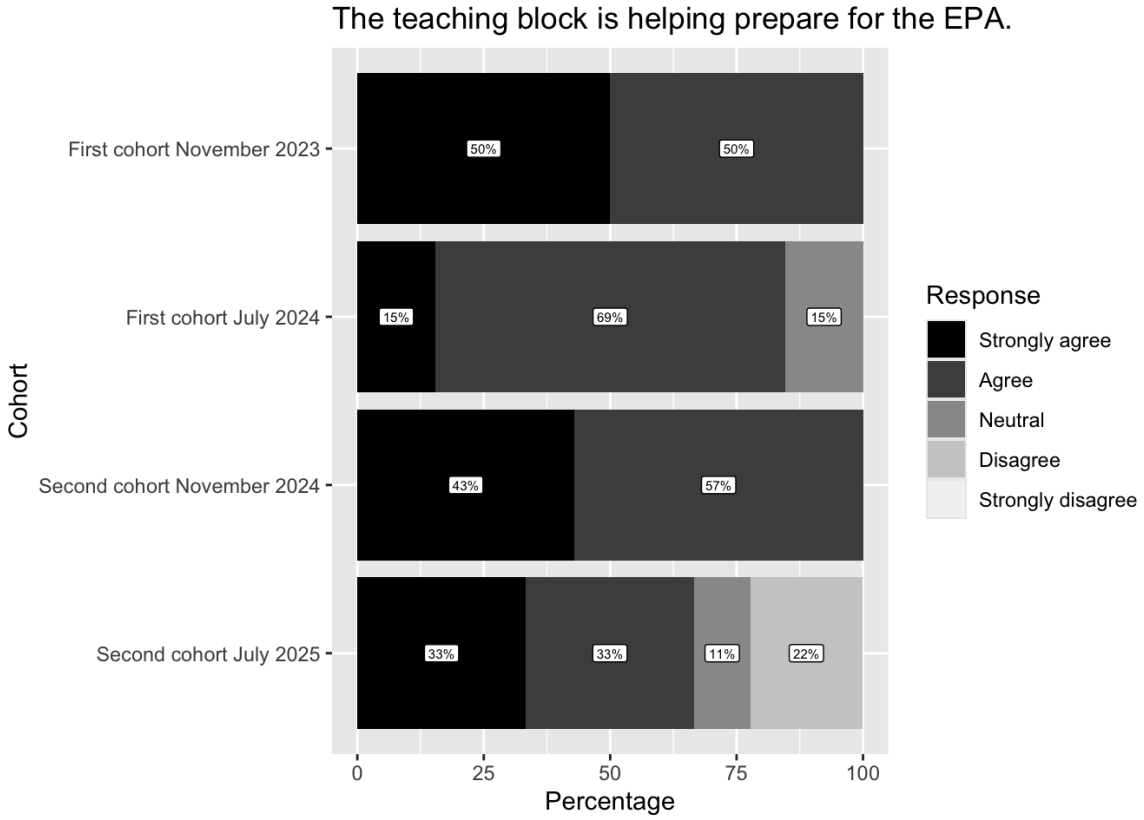


Figure 1. A Likert plot showing the responses of apprentices. They were asked whether they agree or disagree with the statement "The teaching block is helping me to prepare for the portfolio and professional discussion", for the 'Becoming a Professional Data Scientist' teaching block they completed.

Apprentice comments suggested that they valued the structured guidance and mock professional discussions:

> *"Having some support and guidance from the University in preparing for the portfolio/professional discussion is really helpful, so I don't have to guess about what is required."* (Cohort 1, November)

> *"The block release was really useful for understanding the professional discussion. I felt I knew a good amount about the portfolio but there were opportunities to ask questions informally as we went along throughout the day which I liked."* (Cohort 2, November)

Cohort 1 generally appeared more confident:

> *"I am pretty good in an interview and know my projects well, just got to get that last one done."* (Cohort 1, July)
>
> "*I just don't have much experience with vivas."* (Cohort 2, July).

These differences were not surprising due to the general differences of previous work experiences in the two cohorts.

4.2. How did the teaching block contribute to apprentices' sense of preparedness for the future careers as data scientists?

Apprentices found the teaching block beneficial for career readiness, especially the data science guest speaker sessions (Figure 2). However, perceived usefulness declined over time.

> "*Hearing from current Data Scientists was extremely insightful*." (Cohort 2, November)
>
> "*The guest speakers were incredible and I would really like more. I think this should have been implemented in our first year."* (Cohort 1, November)

This suggests that there is some appetite for seeing real data scientists from other work contexts earlier on in the apprenticeship and not just when they are preparing to finish the apprenticeship.

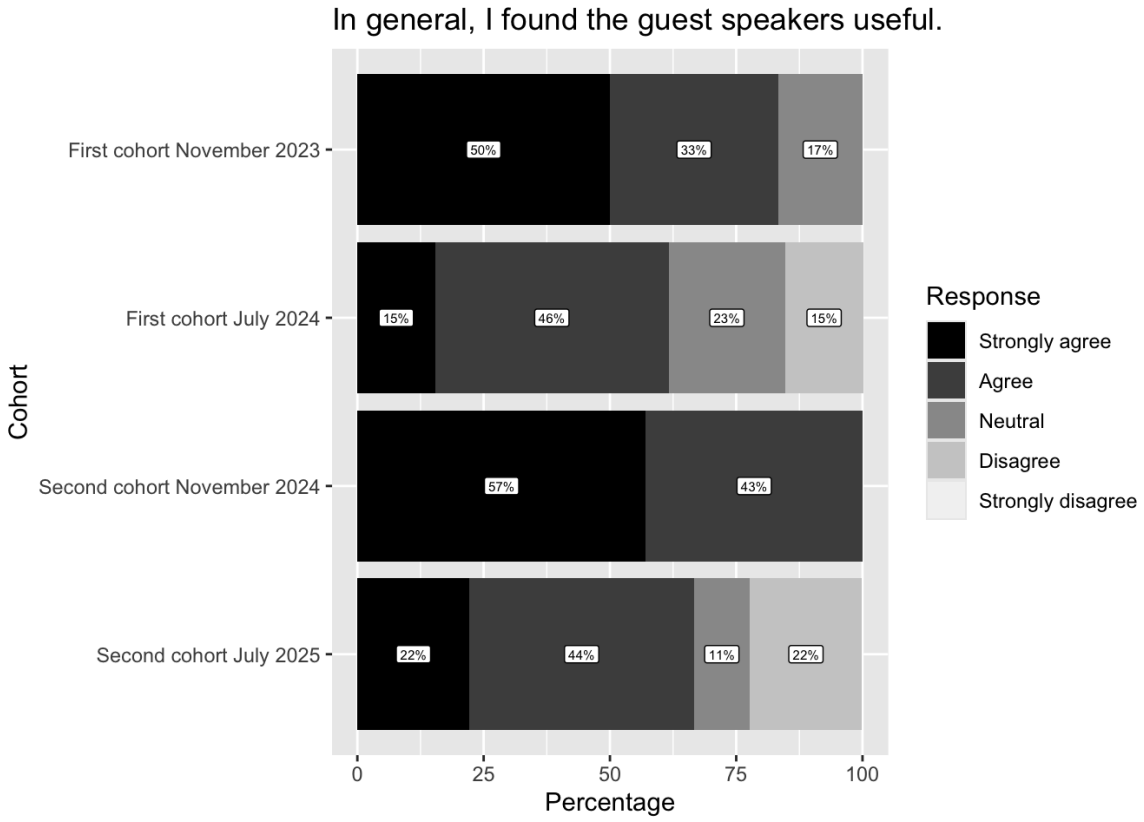


Figure 2. A Likert plot showing the responses of apprentices. They were asked whether they agree or disagree with the statement "In general, I found the guest speakers useful", in the 'Becoming a Professional Data Scientist' teaching block they completed.

There was also strong appreciation for the in-person block release and CV feedback task (Figure 3), though one apprentice suggested improvements, which were implemented in 2025:

> "*I felt that for the block release session where we provided feedback on each others' CVs, it was difficult to understand how I should improve the CV based on the feedback and I couldn't ask the person who provided the feedback for more clarification as it was anonymous. I felt this task would have been better if it were done in small groups of about 3, where the groups look through the CVs together and discuss how to improve them."* (Cohort 2, November)

However, there were some apprentices in Cohort 1 who commented that rather than a teaching block that prepared them for the workplace they would have preferred a teaching block that taught them more technical knowledge:

> "*I think some of the exercises and talks were useful but at the same time I think the study hours could have been spent better teaching us technical knowledge instead. If I had an option between this module and for example another coding module, I would choose the latter*." (Cohort 1, November)

However, others valued the non-technical content:

> "*I think it would have been good to have more non-technical learning like 'Becoming a Professional Data Scientist' throughout the three years."* (Cohort 1, July)

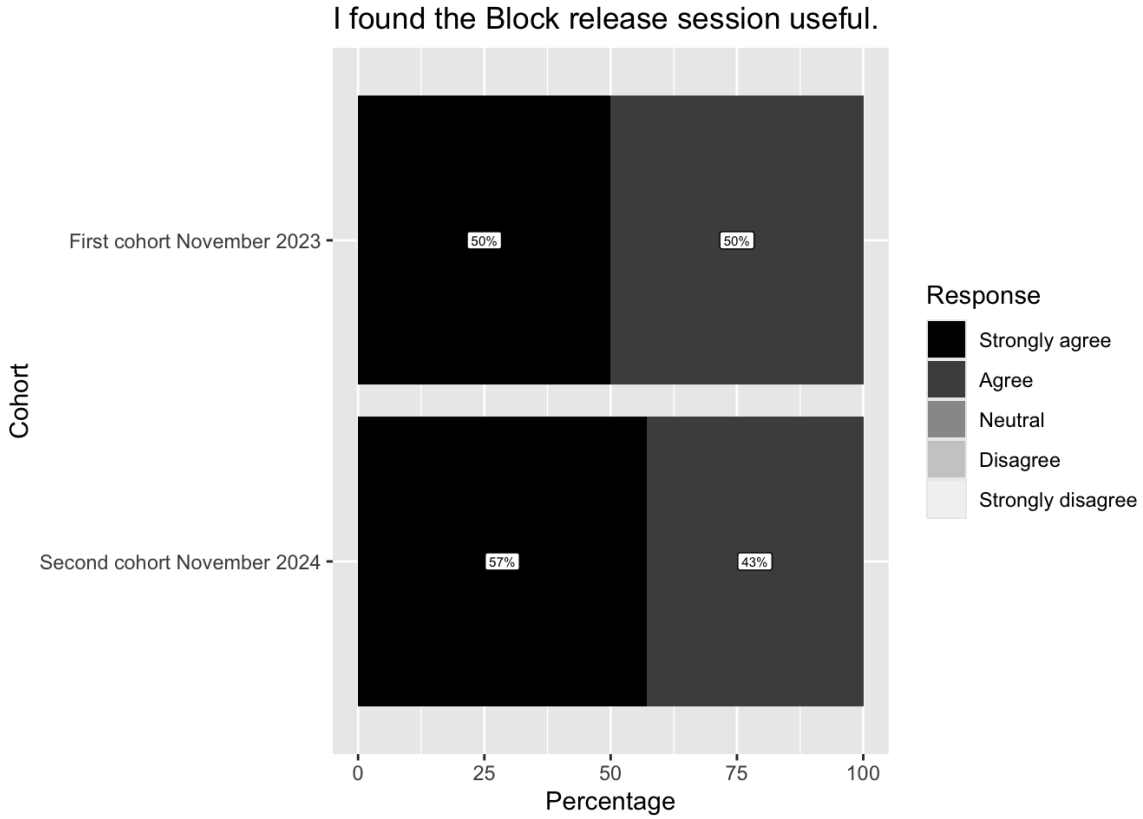


Figure 3. A Likert plot showing the responses of apprentices. They were asked whether they agree or disagree with the statement "In general, I found the Block release session useful", in the 'Becoming a Professional Data Scientist' teaching block they completed.

4.3. Is there a difference between the two cohorts in terms of perceived preparedness for the EPA and future careers?

Cohort 2 were generally more positive immediately after the completion of the teaching block (Figures 2-5), except regarding EPA preparedness (Figure 1), likely due to less workplace experience. Cohort 1, while more confident, sometimes found the content less relevant:

> "*As someone who is not doing their first degree, some of the project support and portfolio teaching blocks were not particularly valuable, although I can see how they may be for others.*" (Cohort 1, July)

In contrast:

> "*I thoroughly enjoyed this learning block as it allowed me to dedicate some time to my personal growth as a data scientist.*" (Cohort 2, November).

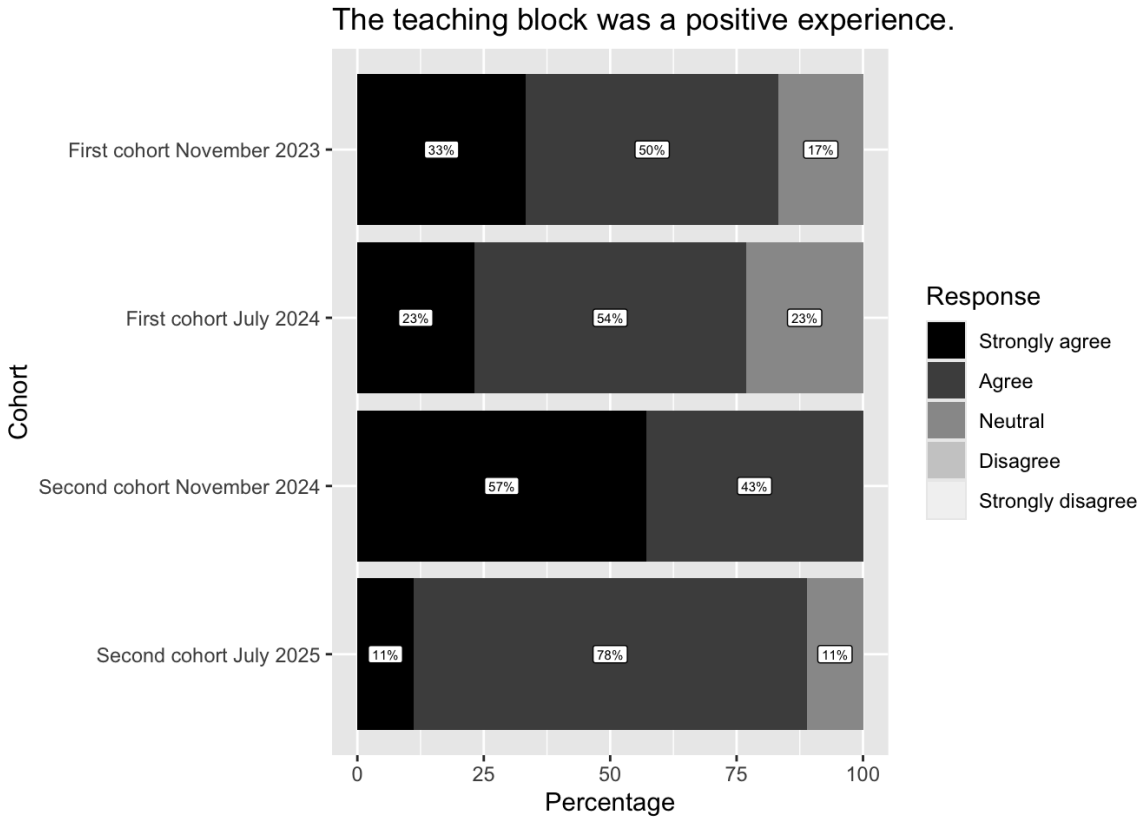


Figure 4. A Likert plot showing the responses of apprentices. They were asked whether they agree or disagree with the statement "The teaching block was a positive experience", for the 'Becoming a Professional Data Scientist' teaching block they completed.

In both cohorts we found that responses around the teaching block, guest speakers and EPA preparedness declined over time (Figures 1, 2 and 4), particularly in Cohort 2, suggesting a need for ongoing support.

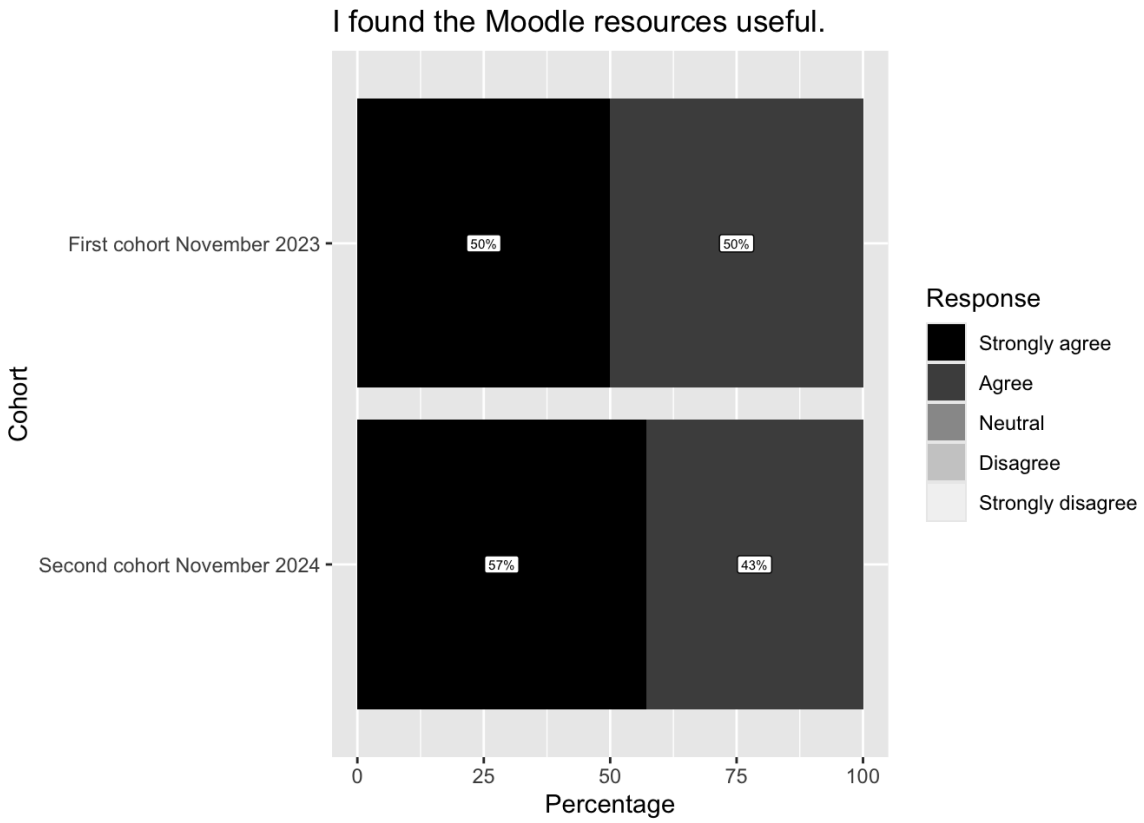


Figure 5. A Likert plot showing the responses of apprentices. They were asked whether they agree or disagree with the statement “In general, I found the Moodle resources useful”, in the ‘Becoming a Professional Data Scientist’ teaching block they completed.

5. Discussion and conclusions

Our analysis set out to evaluate the impact of a dedicated teaching block on apprentices’ preparedness for the EPA and their future careers, and to explore differences between two cohorts. Overall, the findings suggests that the teaching block was effective at preparing apprentices for both the EPA and future careers in the short term. However, the analysis also suggests that there is a slight decline in confidence eight months after the teaching block, particularly in relation to EPA preparation. Perceptions of the teaching block varied with prior workplace experience.

Apprentices found guest speakers from data science helpful for understanding where they are going after the apprenticeship and to see insights from industries that they are not in. In the long term, this exposure may support career progression, especially if apprentices consider changing employers. In-person activities were particularly valued, especially mock professional discussions and evaluating each other’s CVs. However, one consideration in future cohorts has to be diversifying the teaching block so that it is also suitable for more mature apprentices, who are upskilling but have been in the workplace for many years. The second cohort were more positive around the range of activities, but careful evaluation of future cohorts would be required to determine whether this difference is because the teaching block has evolved after feedback, or whether the makeup of workplace experience and age of apprentices is also important in how useful apprentices find the preparation.

The limitation of this analysis is that the sample size is small, although uptake of the survey was very good, particularly in the July surveys. Further investigations with larger, future cohorts, combined

with interviews or focus groups to delve deeper into apprentices' responses would allow for more robust conclusions to be made.

The first cohort of apprentices started in 2021/22 with the fifth cohort of apprentices starting in 2025/26. There has been a significant increase in the number of apprentices in each cohort, with the third cohort to take 'Becoming a Professional Data Scientist' having more than four times the number of apprentices as the second cohort. The teaching block will make use of Power Automate to automate tasks that were done manually before, and will increasingly make more use of tutor feedback, rather than lecturer feedback, with the aim of maintaining the same quality and support as in smaller cohorts. An analysis of student feedback will take place in November 2025 and July 2026 to make sure that students still feel prepared despite the larger cohort sizes.

Although this paper focuses on apprentices already in employment, the teaching block could be adapted for traditional mathematics undergraduate. In fact, this type of learning and development is more important for students without workplace experience, as soft skills are becoming increasingly essential, particularly in the age of AI. (Institute of Mathematics and its Applications, 2021; Robinson, 2024; Walker, 2024).

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CASE STUDY

An update to the design and delivery of an introductory statistics subject for a large student cohort with diverse educational backgrounds and chosen qualifications

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Abstract

This is a case study update on the design, delivery and performance of a first-year undergraduate statistics subject (or course/unit/module), entitled Making Sense of Data, at La Trobe University. This subject is taught both face-to-face and online to a large cohort of students across a number of domestic and international campuses. In order to support the diverse educational backgrounds and chosen qualifications of students, Making Sense of Data contains both a solid foundation of core statistics content, and a stream-specific component. All students cover the core content, and the stream content that best aligns with their chosen qualification(s). This flexible, accessible structure helps ensure that the subject's intended learning outcomes are met whilst highlighting the relevance of statistics for each student's field of study and allowing for stream-specific lectures, assessments and statistical software to be used. In this paper we discuss various feedback-based refinements implemented iteratively in Making Sense of Data in recent years, including adjustments to classes, learning content, assessments, and student support, as well as adjustments made in response to the emergence of Generative AI. We evaluate how these changes to the subject have impacted student outcomes in terms of engagement, satisfaction and performance.

Keywords: Higher education, undergraduate statistics, flexible curriculum, diverse educational requirements, assessment.

1. Introduction

In the era of Big Data and Artificial Intelligence (AI), introductory statistics has become an increasingly essential component of many higher education courses (Tishkovskaya and Lancaster, 2012; GAISE College Report, 2016; Hsu, 2024). Students from all fields of study can benefit from developing statistical literacy, and the abilities to parse data and conduct data-based critical thinking and decision-making are rapidly becoming necessary skills for effectively navigating modern life (Wild and Pfannkuch, 1999; Rumsey, 2002; Fielding, Makar and Ben-Zvi, 2025).

However, the effective delivery of a first-year undergraduate statistics subject (or course/unit/module) remains challenging and complex. Student cohorts are becoming larger and more diverse, and students undertaking their first tertiary statistics subject may exhibit significant variation in terms of their prior mathematical knowledge, familiarity with data, confidence using statistical software, and in their understanding and appreciation of the relevance of statistics within their chosen discipline. These variations can affect student performance, confirming the need for suitable learning environments that offer adequate scaffolding, flexibility and contextual relevance (Bakker and Gravemeijer, 2004; Garfield and Ben-Zvi, 2007). Students' confidence and perceptions toward quantitative subjects such as statistics can also be negatively impacted by prior experiences (Zeidner, 1991; Paechter et al., 2017). Indeed, statistics anxiety is known to be widespread among

first-year cohorts and is typically associated with reduced persistence, lack of confidence, and lower academic success (Onwuegbuzie and Wilson, 2003; Chiesi and Primi, 2010; Macher et al., 2012). To help counteract these issues, research emphasises the value of teaching statistics conceptually and in real-world, discipline-relevant contexts, rather than as procedural instruction, and highlights the benefits of promoting early help-seeking behaviours and effectively addressing and normalising common concerns like statistics anxiety (Cobb, 2007; GAISE College Report, 2016; Vicente et al., 2025).

Assessment structure and type also play a key role in shaping students' early experiences with statistics and in mitigating statistics anxiety. Timely assessment and constructive, supportive feedback can substantially enhance learning, build confidence, and allow students to monitor their progress (Black and Wiliam, 1998; Gibbs and Simpson, 2005; Nicol and Macfarlane-Dick, 2006). In particular, early assessment can be highly beneficial in large cohorts where students may otherwise struggle to measure their understanding of content or may not actively seek individual support. Given the known link between statistics anxiety and procrastination (Onwuegbuzie, 2004), early assessment, for example in the form of weekly quizzes, has been recommended as a useful strategy to disrupt and mitigate this procrastination-anxiety cycle (Chew and Dillon, 2014).

The recent emergence and rapid global adoption of Generative AI (GenAI) large language models further compound the inherent difficulties in teaching statistics effectively. GenAI has created new opportunities and introduced new challenges for subjects across all disciplines in tertiary education, including statistics (Jin et al., 2025; Dunn, 2025). GenAI tools, such as ChatGPT and Microsoft Copilot, can be used as genuinely beneficial tools to enhance students' learning. However, there is a serious risk that without appropriate guidance and support from teachers, these tools can be vulnerable to misuse, leading to issues such as academic integrity violations, over-dependence on GenAI, and the atrophying or lack of development of critical thinking and reasoning skills (Cotton et al., 2023; Kasneci et al., 2023; Sallam, 2023). Therefore, in order for a modern introductory statistics subject to effectively support student learning, it is vital to integrate explicit guidance on the responsible and ethical use of AI into the curriculum (Borenstein and Howard, 2021).

These complexities and challenges highlight the need for first-year statistics subjects that are flexible, adaptable and supportive.

Making Sense of Data (with subject code STM1001) was initially designed in 2020-2021 to meet the requirement for a flexible, scalable university-wide first year undergraduate statistics subject at La Trobe University. The subject needed to support the learning requirements of students with diverse educational backgrounds and chosen qualifications and effectively address statistics-specific teaching challenges such as statistics anxiety. STM1001 also had to satisfy institutional requirements, such as the structural parameters of the university-wide course restructuring that was occurring at this time, and the needs of various stakeholders from numerous departments. These departmental needs were often discipline-specific, and included, for instance, requirements for certain introductory statistical topics and statistical software to be covered, in order for students to gain the requisite statistical knowledge assumed by subsequent subjects in their various courses. These sometimes-disparate requirements needed to be assimilated into the new subject while ensuring that the overarching structure of STM1001 had a core foundation that was robust and adaptable enough to withstand and accommodate unforeseen or emerging challenges such as GenAI. More background regarding the subject development process, including the contextual university requirements and stakeholder needs, can be found in Kuveke, Shaker and Prendergast (2024).

STM1001 was first delivered in 2022, and has now been in existence for four years. At the La Trobe face-to-face and online campuses, it is offered in both of the 12-week semesters of the Australian

academic year. It is also offered as an online 6-week intensive summer term which is mainly for students who need to repeat the subject after unsuccessfully attempting the subject during one of the semester offerings. In addition, STM1001 is offered at partner institutions both nationally and internationally.

STM1001 consists of two components: a core component and a stream component. The core component accounts for approximately 70% of the subject content and assessment, and is taken by all students. It covers typical foundational statistics content including descriptive statistics, hypothesis tests, confidence intervals, *t*-tests, chi-square tests, ANOVAs, and linear regression. The stream component accounts for the remaining 30% of the subject content and assessment. Currently two stream components are offered: the Science/Health (SH) stream and the Data Science (DS) stream. Students are assigned to the stream that better aligns with their chosen qualification(s). Within the stream content, SH students predominantly learn about study design, while DS students learn coding, machine learning, and interactive data visualisation skills. This versatile structure permits stream-specific lectures, computer labs and assessments, as well as allowing for students to learn stream-specific statistical software packages, namely jamovi (The jamovi project, 2025) and R (R Core Team, 2025) for SH and DS students respectively. Table 1 and Figure 1 display the composition of SH and DS students in the Semester 1 (S1) and Semester 2 (S2) instances of STM1001 throughout the years. Student numbers by discipline group over time are shown in Table 2 and Figure 2. To date, over 4900 students have completed the subject, with student numbers growing steadily each year.

Table 1. Overview of STM1001 students by stream over time. Semester 1 and Semester 2 are referred to as S1 and S2 respectively

Stream/Year	S1 2022	S2 2022	S1 2023	S2 2023	S1 2024	S2 2024	S1 2025	S2 2025	Total
Data Science	19	62	44	83	63	108	82	92	553
Science/Health	126	392	464	564	571	750	599	882	4348
Total	145	454	508	647	634	858	681	974	4901

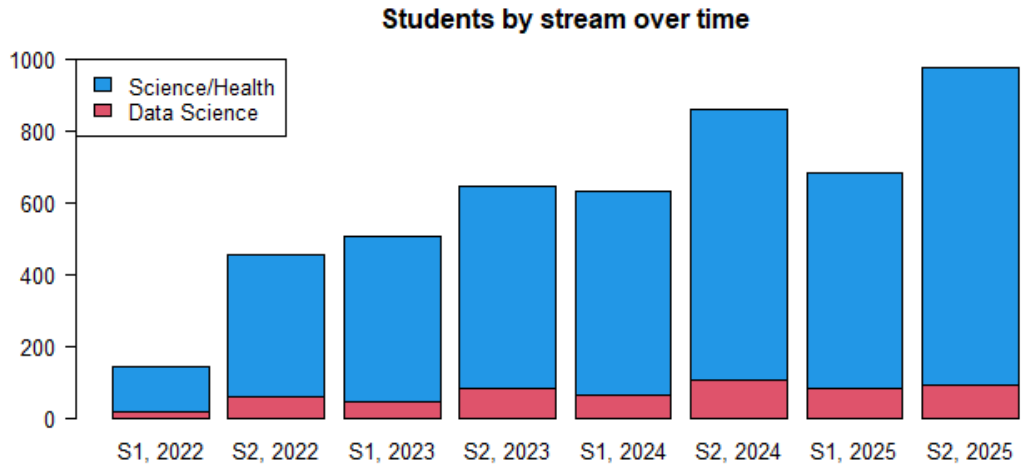


Figure 1. Bar chart of STM1001 students by stream over time. Semester 1 and Semester 2 are referred to as S1 and S2 respectively.

Table 2. Overview of STM1001 students by discipline group over time

Discipline group/Year	S1 2022	S2 2022	S1 2023	S2 2023	S1 2024	S2 2024	S1 2025	S2 2025	Total
Health Sciences	1	22	218	218	302	366	313	431	1871
Life and Applied Sciences	86	266	172	255	162	250	146	278	1615
General Science	48	136	91	119	105	124	93	107	823
IT-related disciplines	8	24	22	47	39	71	47	65	323
Business	1	0	4	4	3	8	15	5	40
Other	1	6	1	4	23	39	67	88	229
Total	145	454	508	647	634	858	681	974	4901

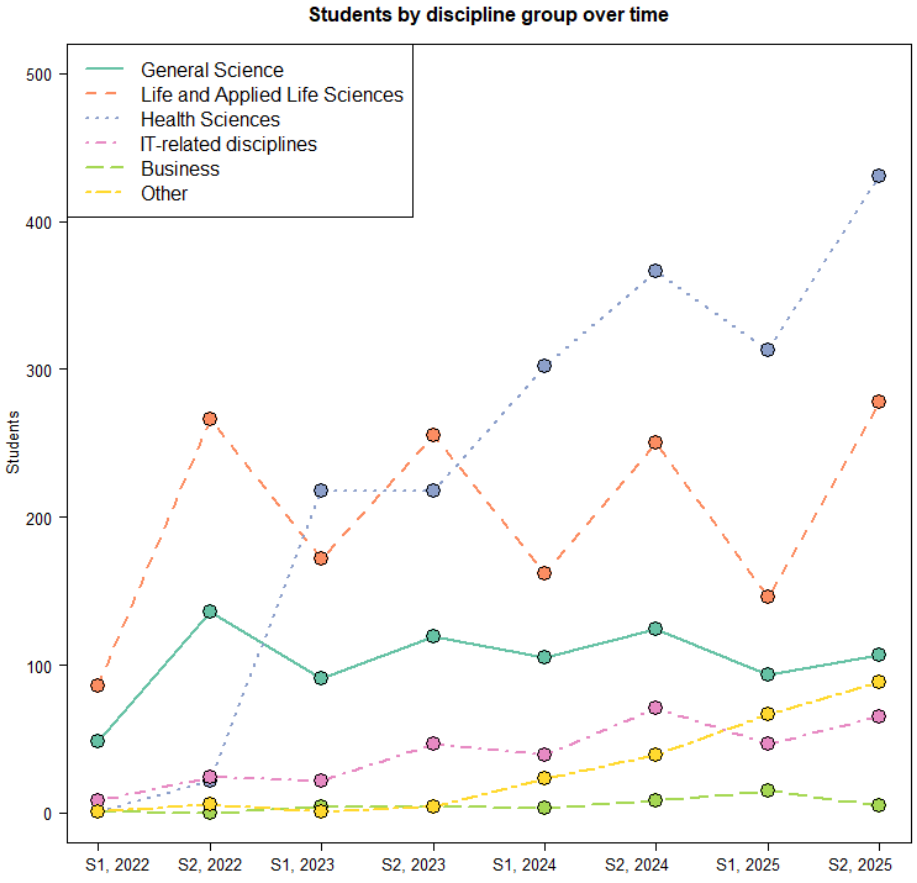


Figure 2. STM1001 student enrolment numbers by discipline group over time.

We previously reported on the design and initial implementation of and results for Making Sense of Data in Kuveke, Shaker and Prendergast (2024). Readers are referred to this paper for further details and discussion on the core and stream-specific design of the subject, the methods used to address

and mitigate statistics anxiety, the open-access nature of the subject's learning resources, and the pedagogical grounds for these design choices.

In this case study update we focus on the adjustments and enhancements made to STM1001 since 2023. These iterative refinements have been driven by student and staff feedback, recent pedagogical developments, institutional requirements, and the ever-evolving higher education landscape in an era of GenAI ubiquity. We outline the adjustments to content delivery, classes, support mechanisms, and assessment structure, and present an evaluation of these adjustments in terms of student engagement, satisfaction and performance.

2. Adjustments

Since we last reported on the design and delivery of STM1001 in Kuveke, Shaker and Prendergast (2024), the subject has undergone a number of further iterative feedback-based adjustments which we present and discuss in this section. Where information is available regarding the evaluation of individual adjustments, it will be provided within this section. An overall evaluation of the adjustments considering student performance and feedback over time will then be provided in Section 3.

2.1. Lecture and Computer Lab Restructure

There has been a significant adjustment to the structure of scheduled synchronous learning activities in STM1001 in recent years.

Originally, in 2022, weekly content was introduced via scheduled 1-hour interactive workshops, following Bergmann and Sams' (2014) 'flipped learning' approach. The workshops were supplemented by two 1-hour computer labs each week. Students were expected to also augment their learning with self-directed study, using the extensive open-access bespoke online resources provided through the subject's Learning Management System (LMS). However, feedback from students and staff highlighted that further direct guidance was required, particularly for topics involving theoretical statistics concepts. Therefore in 2023 we began gradually introducing core and stream-specific lectures to the subject curriculum, while concurrently reducing the amount of content for some topics.

In 2024 we further restructured the scheduled synchronous learning activities by combining the weekly workshops and existing lectures into a set of integrated, interactive weekly lectures. As part of this restructure, new lecture materials were developed for both core and stream content. In 2025, following student feedback, we created two additional DS-specific lectures, which involve interactive elements including collaborative R coding and error debugging, in order to further support students with learning and developing R coding skills.

The weekly lectures are 2-hour synchronous sessions, delivered online via Zoom and recorded, to maximise accessibility for all students across both physical and online campuses. Typically, the first 1-1.5 hours of each session consist of a lecture on core content. This is then generally followed by a shorter lecture on stream-specific content. However, the structure is designed to be flexible such that the length of the core and stream-specific lectures can be adjusted as necessary, dependent upon the specific content covered that week.

Lecture slides are provided to students in pdf format, and are also available publicly on RPubs.com, to cater for various accessibility needs. As part of our ongoing efforts to help address, normalise, and mitigate students' feelings of statistics anxiety (see e.g. Onwuegbuzie and Wilson, 2003; Macher et al., 2012; Marshall et al., 2017), in Weeks 1-7 we include slides with strategies for combating statistics anxiety (Riach et al., 2025), whilst highlighting available support options. We also incorporate Kahoot (an online game-based classroom polling platform, kahoot.com) quizzes into

each lecture to help promote and support student engagement and learning throughout the semester (Shaker, Hurst and Marshall, 2021). Evaluations of incorporating both the Kahoot quizzes and the slides for combatting statistics anxiety have shown a significant, positive impact on students' perceptions of statistics, as discussed in Riach et al. (2025).

In conjunction with the workshop/lecture restructure, the structure of the computer labs was also refined in 2024, with the two 1-hour sessions merged into one 2-hour session. This simplified structure helped further streamline the student experience, with students now required to simply allocate to a 2-hour lecture session and a 2-hour computer lab session each week. This is in contrast to the original, more complicated allocation requirement of a 1-hour workshop, a 1-hour lecture, and two 1-hour computer labs.

The benefits of this comprehensive restructure are five-fold. From the student perspective, (i) the online format of the lectures provides a consolidated forum for the subject coordinator to facilitate and support student learning, and ensures consistency of content delivery for all students; (ii) the study burden on students is reduced, with a more streamlined timetable and less reliance on unstructured self-directed learning; and (iii) students are now guaranteed the same lab demonstrator and classmates for all content throughout the semester, supporting the valuable development of rapport and engagement between students and staff (Mattanah, 2024), whereas previously they could potentially have allocated to two computer labs running on different days with different demonstrators and peers. Meanwhile, from an institutional perspective, (iv) the new lecture format eliminates the need for multiple room bookings and hiring of casual staff to run the workshops, offering significant cost-savings, and (v) the new lecture and computer lab structure supports administrative planning and workload allocations, the volume of which is non-trivial given the cohort size.

2.2. Fostering student interest in statistics

Following student feedback, we identified that some SH students struggled to understand the link between statistics and their chosen qualification. Students who develop a deeper understanding and appreciation of the importance of statistics tend to persevere with their studies and achieve positive outcomes despite feelings of statistics anxiety, as discussed in Marshall et al. (2022). Therefore, to further contextualise the importance and relevance of statistics for students, in 2025 we created 15 short interview-style videos featuring experts from various fields discussing the importance of statistics in their discipline. These videos were integrated into the SH computer labs alongside a reflective activity, and have assisted students in understanding the relevance of statistics to their context.

2.3. A bespoke GenAI Chatbot and other student support implementations

To better understand and meet the diverse and evolving needs of STM1001 students, we have embedded a variety of supports within the subject, including those noted above and in Kuveke, Shaker and Prendergast (2024). Additional, post-2023 implementations and refinements are discussed below.

In Semester 1 2024 we introduced a short survey during Week 3, in which students reflect on their initial progress and experience with the subject. Completion of this survey is required to gain access to the weekly quiz during Week 3. The survey helps us to identify at-risk students and to direct them to the appropriate support services. Based on feedback from the Semester 2 2024 survey, we identified that many students required additional maths skills support. In response to this feedback, we developed an online book with scaffolded maths skills specifically required for STM1001. Students have greatly appreciated this additional open-source resource, which has had significant engagement of over 10,000 views by 2,200 users to date.

In addition to the short Week 3 survey, at-risk students are also identified by their engagement, or lack thereof, with the LMS, alongside their performance with the weekly quizzes (see Section 2.4). Beginning in 2023, an email outreach program has been implemented whereby students are sent personalised emails via either the Student Relationship Engagement System (SRES, Lui et al., 2017) or mail merge. This proactive support mechanism is designed to assist at-risk students to access relevant support, and to also encourage students who are performing well while providing helpful reminders about available support services.

In 2024, to both support students in their transition from secondary to tertiary education, and to help reduce administrative workload, we developed an extensive set of Frequently Asked Questions (FAQs). These FAQs are provided on the STM1001 LMS and cover details on enrolment, class allocation, extension processes for assessments, and available support resources. Streamlined versions of these FAQs are also integrated into autoreplies for the subject email account, and are updated throughout the semester with current relevant information. In 2025 we extended this support resource by introducing a bespoke GenAI chatbot (Cogniti, nd) for dynamic interaction with these FAQs. To humanise and help promote engagement with the chatbot we named it Kit, and suggested students think of Kit as a past STM1001 student offering guidance. Also in 2025, questions were added to the first three weekly quizzes (see Section 2.4) relating to information available in the FAQs. Interestingly, only about 9% of students have chosen to make use of Kit, with evaluations to date indicating that students prefer to use other options for support or finding information, such as the FAQs resource, the new questions related to the FAQs within the weekly quizzes, or directly referring to the information provided on the LMS.

To further promote and incentivise consistent engagement with the administrative-related content provided within the FAQs and the LMS, we also introduced a "badges" system in 2025, with a gamification element. By completing certain tasks within the subject's LMS, such as downloading the Subject Learning Guide or watching the Welcome Video, students earn digital badges, each of which has a specific design and points value. While these points do not contribute to the students' marks for the subject, friendly competition between the two streams is encouraged, to help foster a sense of community, and the accumulation of badge points is promoted in lectures and subject announcements throughout the semester. At the end of the semester, an awards ceremony is held during which students who have received full points are acknowledged and small prizes are awarded. Evaluations so far indicate that students have enjoyed the badges, rating their overall experience at 4.0 on average in response to a Likert scale question asking "*What was your overall experience of the badges?"*, from 1; very negative, to 5; very positive (59 responses across the 2025 combined cohort of 1655, 3.56% response rate).

2.4. Changes to Assessment to support student learning and adapt to GenAI

Since inception, STM1001 has been designed to have scalable, authentic assessments that align with and account for the diversity and size of the student cohort.

In 2024 we refined the STM1001 assessment structure to support student learning, by reducing the number of assessments and increasing the weighting of weekly low-stakes early assessments (EA). The number of assignments was reduced from 4 to 3, with assessment of software skills from the (previously) first assignment integrated into the early weekly quizzes. The number of weekly quizzes was also reduced from 8 to 6, whilst the weighting of each quiz increased from 2% to 6%. The exam weighting was reduced slightly from 30% to 25%, to accommodate the other adjustments. The assessment changes between 2023 and 2024 are summarised in Table 3 below.

Table 3. Overview of STM1001 assessment structure in 2023 versus 2024.

Year/Assessment Type	Quizzes (Best 5 results kept)	Assignments	Final Assessment (Exam)
2022-2023	8 Quizzes (2% each, 10% overall) Due weekly Weeks 1-8	4 Assignments (15% each, 60% overall) Due Weeks 6, 8, 10, 12	30%
2024 onwards	6 Quizzes (6% each, 30% overall) Due weekly Weeks 1-6	3 Assignments (15% each, 45% overall) Due Weeks 7, 10, 12	25%

This feedback-based restructure was guided by pedagogical, student-centric considerations, and offers several benefits over the original assessment structure. Previously, students were not formally assessed on their statistical software skills until Week 6, meaning that students who were not engaged with the computer lab material early in the semester were at much higher risk of falling behind. To address this concern, the early quizzes now incorporate questions in which students must download and analyse data in jamovi/R. These questions assess higher-order critical thinking skills and thus allow us to more swiftly identify and support at-risk students (Nicol and Macfarlane-Dick, 2006). The content is scaffolded to nurture students' confidence in their technical skills (Folwell and Brennan, 2025), and to support their performance in subsequent assessments (McArthur, 2023). Together, these EA weighting adjustments mean that students now can obtain substantially more marks sooner – for example 30% of the subject marks by Week 5, as opposed to only 10% prior to 2024. This ability to achieve more marks more quickly helps foster students' self-efficacy in learning statistics, and galvanises their motivation to do so, which in turn helps to mitigate feelings of statistics anxiety (Chew and Dillon, 2014; Trassi et al., 2022).

Results suggest that the increase in the weighting and cognitive level of early assessment in STM1001 since 2024 has contributed positively to students' motivation, confidence and performance in learning statistics, and has concurrently reduced students' levels of statistics anxiety, in particular anxiety towards the use of statistics software. Further details on the assessment restructure's pedagogical rationale, implementation, and results can be found in Shaker et al. (2025).

In addition to the restructure of the assessments in 2024, and given the emergence of GenAI, some assessment questions were also updated in 2024 and 2025 to incorporate evaluative judgement (Bearman et al., 2024) of GenAI outputs. In particular, in some updated questions students are provided with output from GenAI to a specific question. Their task within such questions is to then critically evaluate this GenAI output. This question type requires students to demonstrate higher-order thinking, and also supports students in developing the important skill of critical thinking, particularly in the context of GenAI usage. Further detail regarding the pedagogical considerations, examples, and practical considerations regarding these changes can be found in Shaker (2025).

2.5. Staff Support and Training

While significant time and effort have been devoted to continual feedback-based adjustments and refinements for the benefit of the students in STM1001, it is important to also acknowledge and support our staff, without whom the subject could not operate. Furthermore, considering the results of Riach et al. (2025), which showed that the human elements of teaching (i.e. attitudes and approachability of teaching staff) are most important to students when considering what helps to

improve their feelings towards statistics, we consider that staff support and training is essential, particularly in the context of large student cohorts and teaching teams. The size of the STM1001 student cohort has grown steadily each year, as highlighted in Table 1 and Figure 1, and this has been matched by a concomitant increase in staffing. The teaching team currently consists of 15-20 sessional staff and 2-5 full-time staff, across multiple campuses. Sessional staff are sourced from a pool of current PhD students and more experienced casual staff. Therefore, each semester typically brings some sessional staff turnover, necessitating ongoing training, mentoring, and support for the team.

In order to foster a supportive staff environment and to help ensure consistency in teaching standards across campuses and teaching periods, we provide staff with professional development and guidance in the form of a formal 2-hour training workshop and a peer observation program. The training workshop was first offered in 2023 and has run at least once per year since. It is held prior to the start of the semester, and covers effective teaching practices, including applying constructivist learning theories (see e.g. Ertmer and Newby, 1993), building rapport and using immediacy behaviours, creating a positive and inclusive classroom environment, marking and feedback techniques, and advice specific to online teaching. To further support staff facilitating online classes, we also provide evidence-based weekly lesson plans. Staff have rated the training as extremely useful, with an average agreement score of 4.75 out of 5 on its usefulness (based on 20 responses from 31 attendees across 2023-2025, 65% response rate). The peer observation program was introduced in 2024 and runs at least once per year. STM1001 staff are paired up and observe their partner's early computer lab classes, and subsequently provide supportive feedback via a structured template. Each staff member concludes the program by writing a short reflection summarising the feedback received, their planned adjustments, and any outcomes of feedback-based changes they have already implemented in their teaching. In combination, these programmes have significantly improved teaching quality consistency, as reflected in the continued improvement in student feedback from 2023 onwards, which is discussed in Section 3.

3. Evaluations

In this section we present data starting from STM1001's inception in 2022, with a focus on evaluating how our sustained, iterative, feedback-based adjustments and refinements implemented since 2023, and discussed in Section 2, have contributed to further improvements in student pass rates, engagement, and satisfaction. For reference, a timeline of these changes is presented in Figure 3 below.

Figure 4 below shows STM1001 pass rates and student feedback scores over time. Specifically, Figure 4A highlights how the pass rate has continued to increase since S2 2023 (78%), with S1 2024 (80.8%) and S2 2024 (82.5%) showing a steady increase before pass rates stabilised in 2025 (S1 (85.5%) and S2 (84.2%)). This consistent improvement in pass rates is linked with a steady improvement in student satisfaction. Figure 4B displays institutional data from Student Feedback on Subject (SFS) surveys, specifically the mean score (out of 5) for responses to the question "*Overall I was satisfied with the quality of this subject*". This score has steadily improved from 3.97 in S2 2023 (114 student responses), to the most recent score of 4.33 in S2 2025 (213 student responses). Given the subject's early undergraduate level, quantitative nature, large cohort size and compulsory status for many students – all factors known to negatively impact student outcomes and satisfaction (see e.g. Neumann, 2001) – the observed changes in SFS and pass rates are non-trivial.

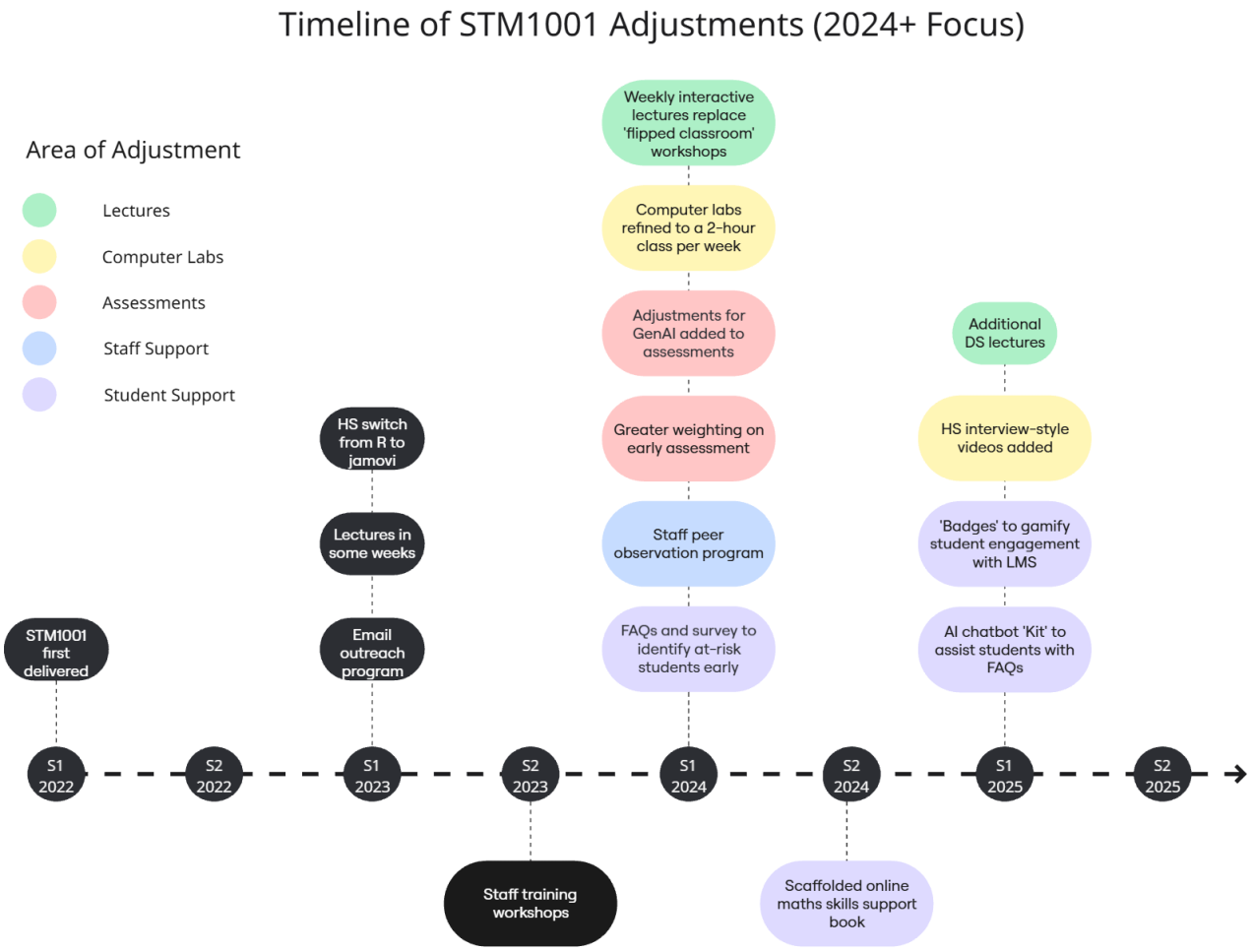


Figure 3. A timeline highlighting the major adjustments and refinements made to STM1001, with a focus on recent adjustments introduced from Semester 1 2024 onwards. Earlier adjustments are noted in black and white.

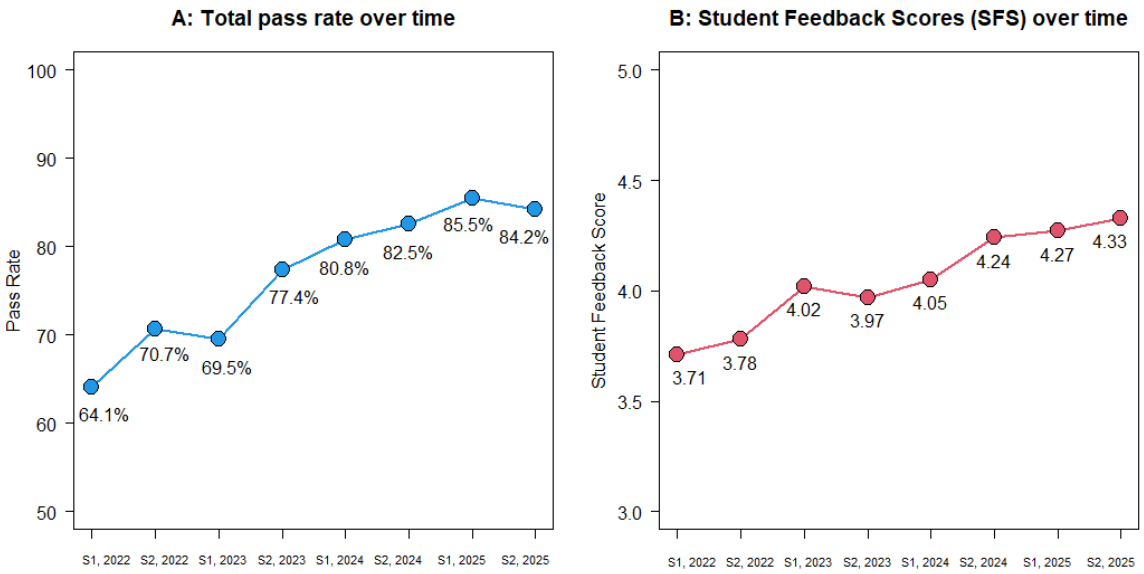


Figure 4. STM1001 pass rates (A) and feedback (B) over time. The Student Feedback score is a mean score (out of 5) in response to the question “Overall I was satisfied with the quality of this subject”.

Given the number of adjustments that have been made from 2024 onward, it is difficult to identify which adjustment (or combination of adjustments) may have led to the observed increases in both student performance and satisfaction. However, based on either formal or anecdotal evidence, each individual adjustment has improved the delivery and student experience within STM1001. We therefore posit that collectively; they have each contributed to the observed outcomes.

4. Conclusion

In this case study update we have outlined the iterative, feedback-based adjustments made to STM1001 following on from the initial design and adjustments discussed in Kuveke, Shaker and Prendergast (2024). A main focus of discussion in Kuveke, Shaker and Prendergast (2024) was the novel, stream-based design of STM1001, which allows the subject to efficiently meet the needs of students from diverse chosen qualifications. As discussed previously, while this structure can introduce additional complexity, along with additional administrative and workload burden for subject coordinators, it can also provide significant efficiency gains from an institutional perspective. With careful design and reflective delivery, this structure can work successfully from both a student and staff perspective.

In summary, the adjustments made from 2024 onwards that we have discussed here include (i) restructuring the class requirements to a simplified 2-hour interactive lecture + 2-hour computer lab weekly schedule, (ii) creation of discipline-specific videos to foster interest amongst the SH cohort, (iii) introducing various additional support mechanisms, (iv) increasing the amount of early assessment to support student confidence and learning, and (v) extending our staff support and training programme. Together with the adjustments made prior to 2024 discussed in Kuveke, Shaker and Prendergast (2024), the most significant of which was changing the statistical software program from R to jamovi for the SH cohort, these adjustments have resulted in sustained, positive impacts in terms of both student satisfaction and performance.

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WORKSHOP REPORT

Teaching students who feel apprehensive towards statistics - what works?

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Keywords: statistics education, statistics anxiety, higher education, relevant data, data visualisation

1. Workshop rationale

Specialist conferences such as the Sigma Network's CETL-MSOR conferences in the UK and The Australian Statistical Conference (ASC) Statistical Education Symposium (SES), bring together experts in statistics education. These forums provide a rich intellectual environment for the exchange of contemporary research, pedagogical innovation, and evidence-based strategies for addressing statistics anxiety (mental distress when encountering statistics, Zeidner, 1991) and students' reluctance to engage with statistics. Workshops held during these two conferences in 2025 aimed to provide a dedicated space for experts to talk and, importantly, document their professional experiences and perspectives so that these ideas could be disseminated to the wider community of Higher Education statistics educators internationally. While research on measuring statistics anxiety is well established (Trassi et al., 2022), less attention has been given to practical approaches that address it (but see Wilson, 1999). Furthermore, much effective practice by educators remains underreported. In this report we fill that gap by distilling practitioner perspectives on addressing statistics anxiety in Higher Education.

2. Workshop design, delivery and analysis

Accepted workshop abstracts, submitted by us as workshop co-organisers, were disseminated through the conference programmes and explicitly invited delegates to participate in these interactive and collaborative sessions. The abstracts outlined that co-organisers would present their work to date on mitigating statistics anxiety to prompt structured discussion and collective exploration of strategies for fostering positive attitudes to statistics. The workshops were 1 hour long. After short presentations highlighting key findings and themes drawn from our research (Marshall et al., 2024; Riach et al., 2025; Shaker et al., 2021; Shaker et al., 2025; Binkowski et. al., 2024) there were two facilitated discussions. The first discussion was prompted by the question: "What have you found that works or what do you think works when teaching students who may feel apprehensive towards statistics?". This aimed to draw out participants' descriptions or ideas of best pedagogic practice. The second discussion, "How can you share and foster best practices of teaching students who may feel apprehensive towards statistics among colleagues or your teaching teams?" concerned how to disseminate this practice and encourage its uptake by others.

Following discussions, participants were invited to type up their thoughts in an online shared document either individually or collaboratively as groups. Access to the shared documents did not work for all participants in the first workshop. Therefore, we advise anyone repeating this method to thoroughly test permission settings are correct. From our experience at similar conferences, we

anticipated people would be eager to share their thoughts; however we were conscious of also wanting to provide for someone to simply engage in discussions without having to record their contributions. We therefore emphasised to participants that the time they were given to record their thoughts could alternatively be used to continue discussions or review contributions from others if they preferred. In addition to participant information on the shared document, the workshop facilitators verbally explained that any written contributions to the shared document could potentially be used in a Workshop Report and that in contributing to the document participants were providing consent. Participants were asked to contribute anonymously and not name institutions to mitigate reputational risks. The project was approved by the Research Ethics Committee for Biological Sciences, University of Leeds (reference number FBS FREC 3263).

The comments contributed by the workshop participants were independently coded by two authors using inductive thematic analysis (Braun and Clarke, 2006), with related or conceptually similar comments identified using a consistent colour-coding system. Three authors then met to discuss the comments and reach consensus on themes. Themes mentioned in at least two participant comments were quantified, serving to consolidate and distil the key themes emerging from the workshops. Comments could be assigned multiple themes where relevant.

To facilitate the dissemination of these discussions among educators, an infographic summarising the comments participants contributed during the workshops was produced with the aid of artificial intelligence AI Infographic Generator (1bit.AI, https://www.1bit.ai/services/ai-infographic-generator) to summarise comments into text and Gemini 1.5 Pro (https://gemini.google.com/) to produce the infographic.

3. Key themes from workshop contributions

A total of 12 and 50 participants attended the UK and Australian conference workshops, respectively. Participants were observed to represent multiple institutions, span the full range of career stages, and comprise a mix of statistics support tutors, statistics lecturers and other educators teaching statistics-related classes, as well as consultants who taught clients. For anonymity, demographic data were not explicitly recorded.

Collectively, participants contributed a total of 3288 words of comments as a mixture of single-line notes and short paragraphs. Examples of participants' comments are presented below under their respective discussion prompt. Where possible, quotes are used to preserve the original meaning of participants' contributions. Citations are provided where further information on a specific practice is available.

3.1 Discussion 1: "What have you found that works or what do you think works when teaching students who may feel apprehensive towards statistics?"

When considering only themes mentioned by at least two participants during Discussion 1, thirteen themes emerged with varying frequency (Figure 1).

There were 20 contributions (Figure 1) that emphasised the importance of using data which was "*tangible real-world examples*", "*tailored for the client's specific domain"* or "*relevant contexts e.g., clinical health".* Some participants explained why this was important.

> *"show them how statistics can make them a better [X] (biologist, ecologist, economist, etc.)"*
>
> *"they are there because they love something else that requires them to study statistics… give them the mathematical tools to do what they love"*

"The examples akin to "pulling coloured tokens from a bag" are not going to get a student inspired and are likely the reason students think statistics is boring and halts any desire for expanding their statistical skills."

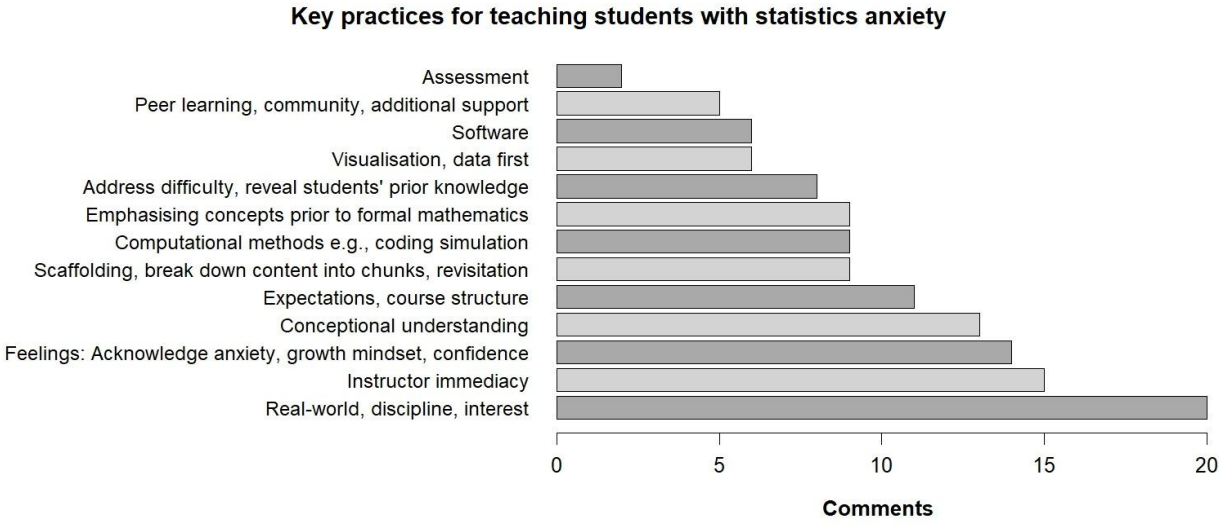


Figure 1. Frequency of themes identified from participants' comments from Discussion 1.

Several contributions highlighted mathematics, particularly the links students make between mathematics and statistics, the focus on fundamental statistical concepts, and the impact of delaying or removing mathematical content, consistent with guidelines for teaching statistics (e.g., Carver et al., 2016).

"Performing simple class activities that demonstrate theoretical statistical concepts and help them see why the math/theory, 'works,'."

"Theoretical mathematics without significant links to outside the classroom creates a significant hurdle for a lot of students who do statistics as part of their degree"

"Take a good, hard look at your course, and ask yourself what students actually need to be able to ,"do stats,", and what remains as artifacts from a world before computers."

Some comments highlighted the power of visualising data for conceptual understanding (Sofroniou, 2025), for demonstrating the application of statistics or for mitigating anxiety by helping students develop intuition that supports their understanding of the underlying mathematics, before engaging with more intimidating, formal mathematical representations.

"I have students start with ggplot to create great graphs and then the stat analysis becomes more understandable."

"Show them the utility of visualising data. Not doing any inferential analysis, just simply showing and understanding the data. Then start adding little elements, building it up little by little."

"Helping students to first see what they <u>can</u> do then build on it. (e.g., if they say 'I can't do stats', show them they <u>can</u> do some e.g., A really bad graph – what is wrong with it"

Participants also described a range of pedagogical approaches using visual or dynamic elements, including using *"simulations to show how statistical tests behave",* creatively displaying information

or using colours to identify key concepts and in one case using, "*live coding*" (Nederbragt et al., 2020).

> "*Visual representation of data and information is important. Not just plots of data, but display of various forms of information"*
>
> *"Overwhelmed by statistical output; remedy for this student was to print out the output and highlight the bits that are relevant"*

There were also comments relating to breaking down or scaffolding learning and recapping on prior content to reinforce learning. Some people gave "*A recap at the start of each lecture*" or "*space for students to ask about topics already covered*" such as "*an anonymous online forum so students can ask questions without being judged*". This technique of breaking down learning into "small steps" was used for "*Getting confidence up early*" or to "*boost your confidence*".

Assessment was discussed less frequently than expected given its importance in teaching statistics (Garfield et al., 2008) with only two comments about "*accessible design*" and *"large numbers/amounts of low-stakes assessments"*. Other comments concerning course structure or design included the choice of software where one participant advocated for the use of "*jamovi/jasp as can be simpler*". One R user emphasised "*that you don't have to be an expert coder*".

In terms of peer learning and community, it was thought that students could *"learn from their peers, assuming class discussions are encouraged*" and people made students aware that peers also have concerns or "*feel anxious*", that "*they're not alone"* and that it should not be a competition.

> *"Students get anxious when they see others ahead of them. It is interesting to contrast this with informing them that others feel the same way. And in fact other students can be very supportive, they might be ahead but still feeling the same way!"*

In terms of supporting students, people were "*offering multiple avenues to help*" and thinking how to make students use the help available.

> *"radical levels of course support with strong built-in mechanisms to force students to use the support as a prerequisite for completing work"*

Beyond considerations of how content was taught or course design, participants also emphasised the importance of *"setting realistic expectations about how fast they will be able to learn"* and stating "*that you are not meant to become experts in stats"* from the start, whilst acknowledging the inherent difficulty of the subject.

> *"The tunnel of statistics can seem long and dark to those that are anxious. I find giving people an early glimpse of how far down the tunnel we're going (this can include saying "were not going beyond X") helps set expectations early and can reduce the anxiety that they might just keep falling and falling into the abyss."*

People also talked about acknowledging students' feelings (Schleutker, 2022) including anxieties, championing a "*growth mindset",* and recognising students' previous experiences.

> *"shaking off prior trauma can be hard, may need one on one, also reassurance that their prior experiences with stats education may have been genuinely terrible - not their skill, the courses they took may have been awful!"*
>
> *Ensure they know stats is not maths. I suspect some of stats anxiety is due to maths anxiety; students thinking that stats = maths."*

One person described their specific method for dealing with fear.

> *"Asking students to reflect seems useful. My first assessment of each term has them write a sentence or two about what they are most fearful about for the course. My final assessment of the term has them write a sentence or two about how it went, and what they think. And a lot of them, given the chance, seem to converge on "this wasn't as bad as I thought it would be!""*

Instructor immediacy is a set of positive verbal and non-verbal behaviours exhibited by an instructor which conveys approachability or availability. These include asking opinions, using names, sharing experiences, making eye contact, engaging in conversation and being available outside class. These are thought to reduce anxiety (Wilson, 1999; Williams, 2010; Riach et al, 2025) and improve student outcomes (McCluskey et al., 2017). Many participants (Figure 1) described aspects of their approach to teaching that reflected immediacy behaviours.

> *"Being approachable and making sure students know we care and want to help"*
>
> *"Introducing myself (family, interests, etc) so I appear more ,'human,'!."*
>
> *"be as not-like-a-mathematician as possible,- welcoming, excited to be there, excited to be teaching the students"*
>
> *"A friendly demeanor is important, as is demonstrating that you will not treat "stupid questions" with contempt. Apprehension of statistics can often be the apprehension of statisticians!"*

3.2 Discussion 2: "How can you share and foster best practices of teaching students who may feel apprehensive towards statistics among colleagues or your teaching teams?"

There were fewer comments in response to the second discussion but these reported colleagues "*shadowing or mentoring*" new staff, "*observing staff from other subjects teaching mathematics and statistics*" and that new tutors "*watch the lecture recordings*" or "*tutorial videos created during covid*". People used "*initial*" or "*weekly meetings*", "*group email*" or a "*message board or chat system*" to communicate and described that this was "*where content is discussed and teaching approaches*" explained.

> *"Mentoring is more based on regular discussions, informal as they are agendaless but formal enough to be regular and booked in. This allows for some organic direction in the conversation and (hopefully - seems to be the case for us) allows the junior person to bring both small and large queries/issues to the table for discussion."*

There was also "*Sharing of resources*", "*provision of materials*" and "*suggested activities each week*".

Two comments acknowledged challenges.

> *"Fear factor - teaching teachers you have to persuade them it's something they can do"*
>
> *"without university not doing a proper training it is difficult to properly train new tutors."*

While many participants discussed developing and mentoring staff, the importance of recruiting the right people was also mentioned.

> *"Some level of progression, so hiring qualified tutors to do the "easiest jobs" first (grading), then moving them on to the tutoring role, and eventually up to the role of lab demonstrator, with experience and proven ability."*
>
> *"recruitment process to assess a person's approach/style to teaching statistics."*

To aid the dissemination of these findings, comments from both discussions 1 and 2 were distilled into an infographic (Figure 2). A high-resolution version of Figure 2 is available to print at https://doi.org/10.5281/zenodo.19946805

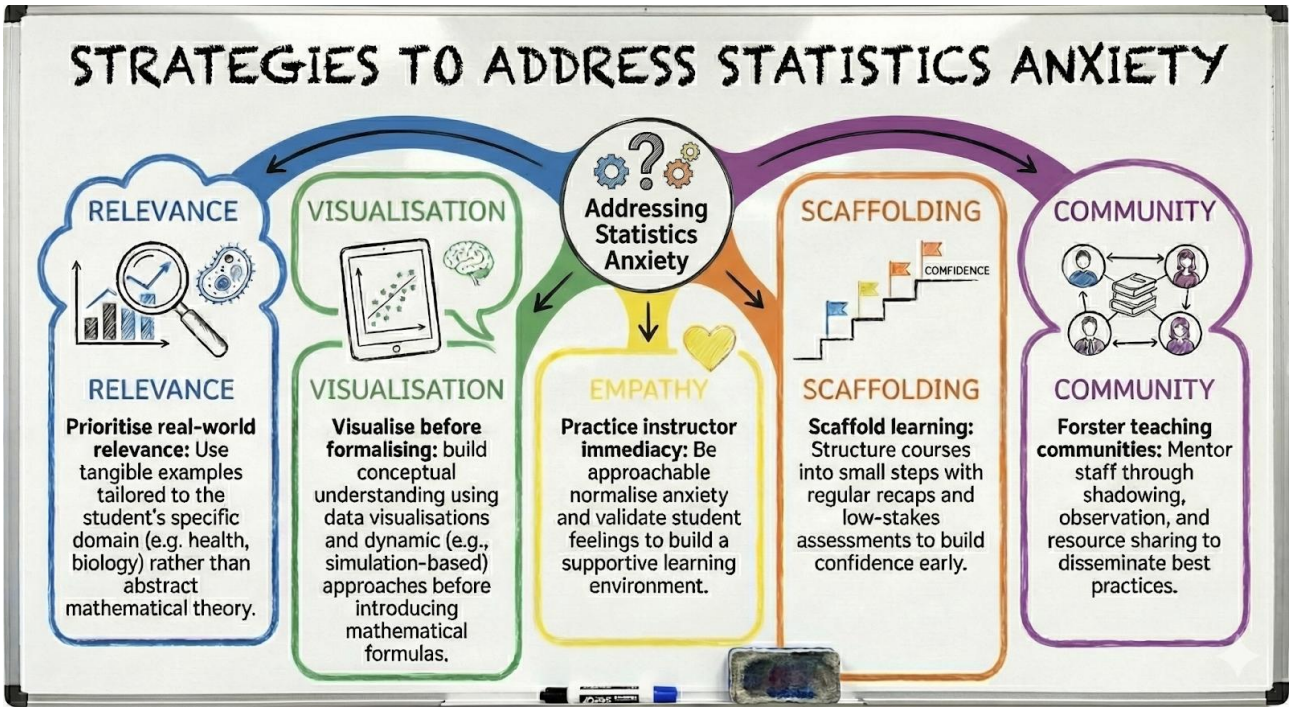


Figure 2. Summary infographic of key themes identified from the workshop's contributions.

4. Final reflection

Previous work has indicated that multiple strategies are needed to address anxiety rather than isolated adjustments (Pan and Tang, 2005; McGrath et al., 2015; Riach et al., 2025). The general themes that emerged from the workshop discussions (Figure 2) align both with this body of prior work and with the GAISE (Guidelines for Assessment and Instruction in Statistics Education) recommendations for assessment and instruction in statistics education (Carver et al., 2016). Specifically, that the focus should be on developing conceptual understanding; using technology, software, and visualisations to understand concepts; scaffolding learning; and analysing authentic data within relevant contexts. The need for breadth in pedagogical strategies is further reflected in the range of methods reported in this work. Practitioner perspectives highlighted that the process of overcoming statistics anxiety starts with explicitly acknowledging and addressing concerns about statistics, and establishing rapport. Foregrounding mathematics and conceptual understanding through visualisation, and the use of authentic, relevant data were among the most widely reported strategies. Instructor immediacy behaviours including attentiveness, approachability and offering additional support were also consistently featured. Together, these results reaffirm and extend individual-cohort studies by consolidating and distilling contributions from a wide range of experiences and Higher Education contexts across the UK and Australia. The contributions are weighted towards the Australian workshop which had more participants, and in choosing to attend such workshops the participants were self-selecting. Since this was a non-random sample, the external validity may be impacted, and the results may not be fully generalisable to the wider statistics education community. Nevertheless, the findings provide a trans-national, practitioner-informed perspective that highlights the value of integrating pedagogical, relational, and structural strategies to address statistics anxiety.

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