

# Towards a Framework for Teaching Artificial Intelligence to a Higher Education Audience

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Artificial Intelligence and its sub-disciplines are becoming increasingly relevant in numerous areas of academia as well as industry and can now be considered a core area of Computer Science [84]. The Higher Education sector are offering more courses in Machine Learning and Artificial Intelligence than ever before. However, there is a lack of research pertaining to best practices for teaching in this complex domain which heavily relies on both computing and mathematical knowledge. We conducted a literature review and qualitative study with students and Higher Education lecturers from a range of educational institutions, with an aim to determine what might constitute best practices in this area in Higher Education. We hypothesised that confidence, mathematics anxiety and differences in student educational background were key factors here. We then investigated the issues surrounding these and whether they inhibit the acquisition of knowledge and skills pertaining to the theoretical basis of artificial intelligence and machine learning. This article shares the insights from both students and lecturers with experience in the field of AI and machine learning education, with the aim to inform prospective pedagogies and studies within this domain and move towards a framework for best practice in teaching and learning of these topics.

CCS Concepts: • **Social and professional topics** → **Computing education**; • **Computing methodologies** → *Artificial intelligence*.

Additional Key Words and Phrases: Artificial Intelligence, pedagogy, self-efficacy.

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## 1 INTRODUCTION

The field of Artificial Intelligence (AI) endeavors to not only try to understand what constitutes intelligence, but to create and build intelligent systems [77]. Within the field of AI there are a number of specific application areas such as robotics and computer vision as well as domains such as machine learning (as shown in Figure 1). Machine learning is “a branch of artificial intelligence that allows computer systems to learn directly from examples, data, and experience” [93]. This capability enables computers to perform tasks by learning from data instead of using pre-programmed rules. Within machine learning, is the field of deep learning which has contributed to the resurgence in the use of AI due to its advances and phenomenal successes in fields such as computer vision, boosting the application of this technology within industry and increasing the popularity of the subject amongst students. For the sake of clarity, AI will be used to denote courses encompassing machine learning and deep learning throughout this paper, without loss of generality.

Individuals with knowledge and experience of AI are highly sought after within industry and the current skills shortage within this sector is becoming an increasing problem for recruiters, with the demand for specialists rising

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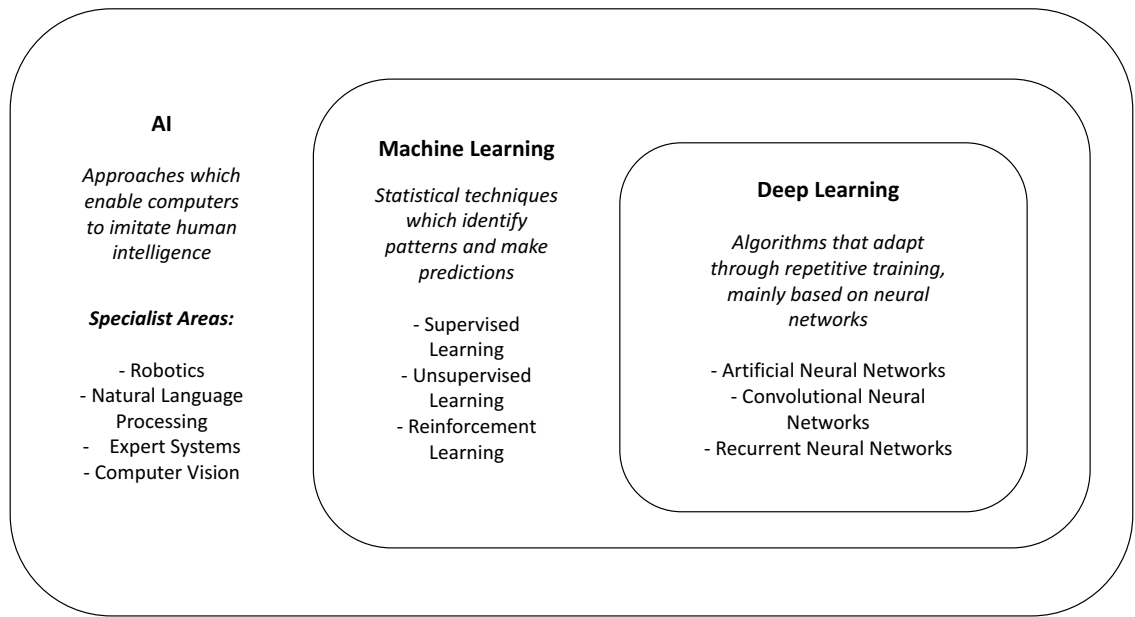


Fig. 1. Overview of AI, Machine Learning and Deep Learning (based on [15][48])

as the UK digital economy grows [26], the same trend is assumed for the rest of the world. Interest in this subject at Higher Education (HE) level is also increasing, resulting in many educational institutions offering some form of AI course, for example, in the UK in 2017 there were twenty-six universities offering undergraduate courses in AI and more than thirty graduate programmes running across twenty universities [42]. More recent findings in 2021, suggest that there is a demand to expand places by a “five to tenfold increase” [94]. However, whilst the uptake of AI courses has been increasing steadily, the number of students taking such courses is still not enough to fill the UK skills gap and “estimates both of potential and predicted growth in the use of AI in the UK would require significant increases in numbers at both levels [Undergraduate and Postgraduate] to be realised in practice” [35]. There is a similar trajectory in the US and European Union [85], 93% of US and UK organisations state that they consider AI to be a priority to their business, however 51% acknowledge that they do not have the right amount of staff to implement their AI strategies [8].

Two issues that may impact on attracting and retaining students within this topic are 1. the best practices in pedagogy to teach the specialist skills required are still relatively unexplored, 2. AI is an advanced subject that combines aspects from both mathematics and computer science where students may lack confidence in their ability to do well in such courses, especially if they suffer from mathematics anxiety or have a general lack of confidence in their technical skills. Mathematics anxiety “involves feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of mathematical problems” [73]. The level of mathematics and computer science required to understand and execute machine learning is often not taught within a single course. The level of technical skills required by the student is determined by the type of AI course they are undertaking. There are two main strands of AI education, how to apply these techniques and how to create and innovate new AI methodologies. The prerequisites will differ based upon the type of AI course with the latter requiring greater in-depth mathematical knowledge.

## 1.1 Case Study Overview

In our study, qualitative research and existing studies have been used to determine the opinion in the scholarly community regarding this technology. Determining any misconceptions prospective AI students may have will help to identify the already embedded mental model and inform on the need to clarify any misinterpretations. Gaining a greater understanding of the opinions of AI may also lead the development of strategies to encourage more people to become skilled – thus accommodating the rising demand. The case study will aim to provide findings relating to the two issues identified in the previous section in relation to attracting and retaining students.

Recent surveys undertaken by Cameron [12] and Ipsos MORI [45] indicate that individuals who could be deemed “digital natives”, a term coined by Prensky [68] to indicate individuals who grew up with computer and internet access, are more familiar with the term machine learning. These studies also indicated that the participants were not particularly interested in how machine learning worked, this was “in part due to the complexity of the technology being something they assumed they would not be able to understand” [12]. The opinion that machine learning is too complex to understand may be an issue with the recruitment of appropriate candidates to courses. It may also lead to confidence issues amongst students who are undertaking an AI module but who are not specialists in computer science and are studying another domain.

Investigating the prior mathematics attainment level of students on AI courses, alongside the current UK HE offerings in mathematics could determine whether there are any topics or skill gaps which could lead to difficulties for students taking these courses. Data science courses were also reviewed as this field is “still in its formative period” [98] and there is yet to be a definitive definition of the tools and methods within this discipline, however, some data scientists are competent in machine learning [28].

We set out to understand some of the barriers students may face when trying to learn AI. We particularly focused on confidence level and self-efficacy and how this might impact their willingness or ability to learn. Steven [88], advises that “there will rarely be only one barrier facing a particular group,” instead students are perhaps encountering a number of barriers which may amalgamate. Prior research pertaining to barriers students may face often use a deficit model, where the underrepresented group are charged with overcoming these issues, “rather than assessing the impact of institutional infrastructure, entry requirements, course structure and student experience” [88]. We also investigated metacognition which is our “ability to articulate and regulate the mental processes that we use to construct our knowledge, understanding and skills” [58]. Metacognition, self-regulation and self-efficacy are concepts which have been identified to “help students to organize their study activity independently and effectively” [14]. We decided to look at these factors as well as the personal experiences and capabilities of the students themselves. To do this we used AI/machine learning modules at three different universities as our case studies. In the case studies we used student questionnaires, observation, and interviews with the lecturers within two undergraduate modules and one postgraduate module, however there were limitations to data collection due to student participation being optional.

We believe that the identification of the threshold concepts within this domain will enable better teacher understanding of the specific topics that can cause students difficulty and help guide future learning design and best practice. Threshold concepts often cause difficulty for students but can also lead to greater understanding of key ideas within the field of AI if taught effectively. Walker [96] advises that threshold concepts are usually the parts of the course where students ‘get stuck’ and that they can be regarded as a “particular state of expert knowledge.” Students who have not yet fully understood a threshold concept attempt to learn new ideas in a more disjointed manner as they cannot yet integrate

157 this new concept into their way of thinking. Students with sophisticated metacognition will be equipped to navigate  
158 through threshold concepts as metacognitive processes are “associated with enhanced cognitive performance” [58].

159 Once the threshold concept has been comprehended, the student can then integrate different aspects of the overall  
160 subject into their analysis of problems [51]. Preparing for threshold concepts within lessons should ensure that lecturers  
161 can implement strategies to aid students when they encounter these concepts, demonstrating that they can tolerate  
162 learner confusion [21] and help them formulate differing approaches to better student understanding. Students’ can often  
163 have a muddled path towards learning which, unless communicated to the lecturer, can often lead to miscommunication  
164 regarding student progress [57].

165  
166 This paper contributes to the limited research relating to teaching AI and outlines an initial framework of the best  
167 practices for teaching in this domain through identification of barriers students encounter within AI courses. To aid the  
168 design of our study we reviewed previous work in the area. Section 2 provides a literature review relating to education  
169 and the potential barriers students and lecturers may face. Section 3 details the research methods used in this study to  
170 determine the current provision relating to AI education and experiences of students and lecturers. Section 4 describes  
171 the current pedagogical offerings within this domain and the results from student and lecturer interaction. Sections 5, 6  
172 and 7 discuss the overall findings of the research, the limitations of this study and future work.

## 176 2 BACKGROUND

177  
178 A literature review was carried out to determine current practice and existing research within the field of AI and  
179 education. Keywords were identified to construct a search strategy pertaining to AI, these included ‘artificial intelligence’  
180 and disciplines within this field including ‘machine learning’, ‘deep learning’ and ‘data science’. The field of data science  
181 was included as it can cover a multitude of topics from collecting, cleaning and analysing data and often application of  
182 a range of machine learning techniques [78].

183  
184 The term *Artificial Intelligence* was conceived of in 1956 at the birthplace of the field, Dartmouth College, by John  
185 McCarthy. Alongside colleagues McCarthy hosted a two-month project relating to the study of AI. Following a number  
186 of successes, AI became a booming industry during the 1980’s, however companies failed to deliver on their excessive  
187 promises leading to what was termed the “AI Winter” [77]. However, recent changes in technology and the arrival of  
188 Big Data [59] has led to a resurgence in AI popularity and it is now viewed as a solution to a large range of problems,  
189 consequently becoming embedded within the infrastructure of a range of industries.

190  
191 Due to the AI resurgence, inclusion of AI within the HE computer science curricula has been expanding and the  
192 popularity of these courses fast increasing with a number of universities now offering AI specialisms. However, there  
193 is a need for more AI based courses, including MOOCs (Massive Open Online Courses) and continuing professional  
194 development courses to increase the number of people trained with these specialist skills [35]. To take advantage of AI  
195 technology, and for this domain to be widely accepted and disseminated, a significant proportion of the population need  
196 to be trained in this area [53]. Relatively little research has been undertaken regarding the best practice for teaching AI,  
197 with an increasing demand for graduates with these skills it is important to analyse how these topics are currently  
198 being taught and gain comprehension of the staff and student experience.

199  
200 A review of the recent literature produced very little in terms of identifying educational best practice relating to AI,  
201 we therefore widened our search to include related topics within computer science, particularly data science courses.  
202 We felt this would give a clearer understanding of the difficulties faced by students of similar topics, which may also  
203 arise on an AI course. We also identified current practice within computing education leading us to the hypothesis that  
204 mathematics anxiety and low confidence may be a deterrent to studying AI and may also cause difficulties for students  
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209 on these courses. It has been shown that self-efficacy and self-regulation are intrinsically linked to mathematics anxiety  
210 [47], therefore strategies to improve student self-efficacy, in turn leading to further self-regulation may be an appropriate  
211 mitigation strategy. Academic self-regulation involves awareness and orientation of both cognitive and metacognitive  
212 processes alongside execution of appropriate learning strategies to achieve specific learning outcomes [47][65]. Even if  
213 the hypothesis of mathematics anxiety does not hold true, improving student self-efficacy and self-regulation will better  
214 equip students in their learning. Identifying the potential threshold concepts is an important step towards a framework  
215 of best practice within AI as it will enable course leaders to focus on topics which are integral to understand the field  
216 [21] and plan strategies to ease the students through the transitional liminal space.  
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## 2.1 Overcoming Mathematics Anxiety and Improving Student Confidence

  
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222 *2.1.1 What is Mathematics Anxiety?* Mathematics anxiety can be related to a number of negative consequences  
223 including avoidance of subjects which contain elements of mathematics [2] and can affect the success of the most  
224 intelligent and determined students [44]. Mathematics anxiety is a prevalent issue in the UK, with around 20% of people  
225 experiencing difficulties in this area, the percentage rises to up to 35% among the younger population [6]. The variability  
226 of course cohorts in respect to societal and educational environmental background has also been shown to be linked  
227 with educational motivation constructs including self-efficacy and anxiety relating to mathematics [54]. For example,  
228 mathematics self-efficacy and anxiety can be related to the “notion of culturally diverse sources of self-formulation” [54].  
229 In turn, there is a correlation between anxiety and self-efficacy and the influence on academic performance, particularly  
230 in mathematics [46]. One of the possible factors of this is that students who possess a high level of self-efficacy usually  
231 show greater persistence and more sustained effort when faced with educational challenges [67]. A study by Hunt et al.  
232 [43] into mathematics anxiety levels within the British undergraduate student population indicated that “maths[sic]  
233 anxiety was significantly greater in women than men.” An unanticipated finding from the study by Hunt et al. was  
234 the prevalence of mathematics anxiety among students studying within the science faculty, this was higher than  
235 anticipated. An analysis of current AI education provision will determine the expectation of mathematics skill level for  
236 students within this domain as well as identify specific mathematical content taught within these modules. Determining  
237 demographics, mathematics attainment level and confidence in mathematics skills with case study participants will  
238 identify a profile relating to mathematics for the cohorts studying on these specific AI modules.  
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244 *2.1.2 Strategies to Alleviate Mathematics Anxiety.* A number of strategies to alleviate mathematics anxiety have been  
245 trialed. These interventions include strategies aimed at affecting the whole class through curriculum changes and  
246 experimentation with differing psychological treatments [40][72][79]. Psychological interventions in the literature  
247 varied between behavioural strategies aimed at alleviating negative emotions towards mathematics and cognitive  
248 models which attempted to relieve concerns expressed by the student [40]. Psychological treatments which proved the  
249 most effective in tackling this anxiety included systematic desensitization, increased mathematics exposure, anxiety  
250 management and relaxation training [40][72]. One of the main shortcomings of these methods is the requirement of  
251 specially trained staff who may not be available to carry this out. Lowering student levels of mathematics anxiety can  
252 show improvement and increases to mathematics assessment scores [40]. Ramirez [72] suggests that poor self-regulatory  
253 processes in students can lead to lower perception of personal competence. Implementing strategies for improving  
254 students’ self-efficacy may ease mathematics anxiety and boost student confidence in their mathematics ability, this is  
255 relevant to the issues outlined in the Introduction which may impact on attracting and retaining students. Classroom  
256 interventions and curriculum strategies aimed at reducing mathematics anxiety include the use of games and interactive  
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platforms, providing specialist equipment and using different techniques for delivery of course material (e.g. group work or tutorials) [40][72]. Refreshing the format of lessons is an easy objective, likewise the use of interactive platforms and peer interaction may provide an attainable way to reduce mathematics anxiety within AI courses. We investigated the prevalence of this approach within the case study. Differing pedagogical approaches relating to changing student mind-set have also been trialed such as changing the perception of failure as an important positive learning process and the viewing of mathematical problems as a challenge rather than a threat [72]. To identify cognitive changes in students, lecturers need to be familiar with a range of learning interventions, such as; determining a student's prior understanding when they are approaching a task, having a comprehensive understanding of the material so that they can provide meaningful and challenging experiences to ensure progressive development and identifying when a student has completed the learning outcomes [37].

Approaches such as retesting and self-paced learning have been shown to reduce a student's mathematics anxiety [44]. Retesting is a tool used to motivate students to relearn to a mastery level, skills and concepts which they had not initially fully comprehended [50]. Self-paced learning can alleviate mathematics anxiety through alignment with learning goal orientation instead of performance goal orientation [44]. These approaches will be considered for implementation if a prevalence of mathematics anxiety is found in the case study. The use of distance learning incorporating technology has also been shown to be a successful strategy due to the "anonymity of an online course" [44]. Distance learning can be thought of as the provision of education at a geographically distant location, it often encompasses different learning mediums to provide a range of educational circumstances [62]. Taylor and Mohr [89] created an online distance learning mathematics course which used student centered strategies such as informal language, relevant contextual materials and reflective practice techniques with the dual aim of improving students' mathematics knowledge as well as alleviating mathematics anxiety. 90% of the students reported that the course had improved their confidence relating to mathematics. This research also suggested that distance learning may be more encouraging for students who are reluctant to discuss their past mathematics issues within a classroom environment.

*2.1.3 Key Points.* The presence of mathematics anxiety can impact upon the attainment of students and is interlinked with self-efficacy, a construct which also influences performance. Therefore, it is important within the case study to determine the pervasiveness of mathematics anxiety within current AI cohorts. There are a number of approaches to alleviating mathematics anxiety such as psychological interventions, pedagogical approaches and self-paced and distanced learning. Distance learning as a method for alleviating mathematics anxiety seems the most relevant approach in relation to AI at HE level as this approach can encompass a number of the other strategies such as retesting, self-paced learning and interactive games. The use of this method may play a key role in the framework for teaching AI as a learning resource to assist lecturers in leveling up student's mathematics knowledge. Tackling mathematics anxiety is pivotal as it can impact upon other areas of study which contain threshold concepts with some form of numerical content [70]. If the threshold concepts within this domain are identified and have a mathematics focus, then strategies can be implemented to assist the learner in mastering the threshold concept.

## 2.2 Threshold Concepts

Threshold concepts can be identified through a set of characteristics which define them as core concepts which potentially impede learning. These characteristics are defined as transformative, irreversible, integrative, bounded and potentially troublesome [61]. The main property of a threshold concept is its transformative nature, ensuring that a previously inaccessible way of thinking about a specific topic occurs. The irreversible tendency of threshold concepts

313 ensures that once a topic is understood it cannot be ‘unlearned.’ Comprehension of a topic considered a threshold  
314 concept can reveal relationships between subject areas which were previously thought of as disparate, however threshold  
315 concepts can also be bounded, meaning that each concept does not generally explain the complete discipline. The basis  
316 of a threshold concept is that it is inherently troublesome to learn, sometimes the concept may be counter-intuitive to  
317 beliefs a student may already have regarding a specific subject [4].  
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319 The key threshold concepts relating to AI have not yet been clearly determined. Identifying the troublesome aspects  
320 of this field will enable greater understanding of the difficulties both students and lecturers may encounter within  
321 education in this domain. Awareness of these threshold concepts may also signpost possible strategies for lecturers  
322 to implement to aid students in overcoming these difficulties. For example, object-oriented programming has been  
323 identified as a threshold concept in computing through interviews with students, this enabled instructors to blend this  
324 concept within a context which may be more easily understood [9]. A threshold concept is rarely acquired straightaway  
325 but requires an amount of time for the student to make the transition. This transition period is referred to as the liminal  
326 space and it is in this point that a student is likely to encounter difficulties, including a significant emotional reaction to  
327 this transition [76]. A consequence that is important to consider is that surface level learning may occur as a result  
328 of lecturers incorrectly assuming that students have overcome a threshold concept [9]. Chin [16] defines a student’s  
329 approach as surface learning when they “tend to memorise discrete facts, reproduce terms and procedures through rote  
330 learning” and the student fails to link the specific exercise in relation to their wider learning. Correlating new learning  
331 with previous knowledge may be an important aspect of learning AI and overcoming threshold concepts, particularly  
332 in respect to prior learning in mathematics. Implementing custom learning designs to support students through the  
333 threshold concepts may include a heavier focus on improving students’ metacognition and self-efficacy to give them  
334 the tools and confidence to push through the threshold concept and support their transition to assimilated knowledge.  
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### 341 **2.3 Metacognition, Self-Efficacy and Self-Regulation**

342 “Metacognition refers to the ability to reflect upon, understand, and control one’s learning” [81]. This is an important  
343 technique which enables learners to self-monitor and self-regulate to advance a skill set [80]. The aim of metacognition  
344 is to aid individuals in their awareness, allowing them to plan and monitor their learning, which can directly improve  
345 their performance [81]. Metacognition also encompasses the relationship “between a student’s confidence and their  
346 performance [55]. Self-efficacy and confidence measures are related as students are inherently required to express a  
347 level of confidence when solving a specific problem posed to them, moreover students’ self-judgements of their own  
348 confidence level implores the student to monitor their metacognition [86]. Confidence as a construct ‘represents an  
349 accumulated experience that is used profitably in the process of decision-making’ [86]. Therefore, issues relating to  
350 confidence level can adversely affect student decision making, hindering learning progress as students may wrongly  
351 assess their confidence level.  
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355 Understanding any deficits students have in their self-regulating techniques may help to inform pedagogical methods  
356 to aid students in overcoming threshold concepts. For example, helping students to reflect on their learning may  
357 highlight specific areas which require further attention. Self-regulation entails the “monitoring and managing of one’s  
358 cognitive processes” as well as control over factors such as emotions, behaviour and environment pertaining to learning  
359 [63]. We believe that the processes and understanding which occur through self-regulation may aid students in their  
360 navigation of the liminal space when acquiring a threshold concept. This is out of scope for this study; however, it is to  
361 be explored at a later date.  
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365 2.3.1 *Strategies to Improve Metacognition, Self-Efficacy and Self-Regulation.* The proliferation of technology within  
366 learning has enabled various new learning techniques to be trialed. The use of this technology can improve student  
367 self-monitoring through the use of quizzing with immediate feedback and gamification. These techniques have also  
368 been linked with motivation through new insights into the human reward system, findings demonstrate that motivation  
369 provided by games of chance generate additional dopamine [49].

371 There are a number of strategies based around the concept of improving student’s metacognition and ability to  
372 self-regulate their learning, one of these is the use of problem-posing education, recommended by Freire [30] as opposed  
373 to banking education, where education becomes an act of depositing information [31]. Problem-posing education  
374 bolsters students critical thinking and “stimulates true reflection and action upon reality” [30]. Teaching metacognitive  
375 strategies within the context of the specific course discipline has shown impressive results in that students who  
376 participated in this particular study achieved significantly higher grades than non-participants [95]. The metacognitive  
377 strategies used included social interactions which promote the transfer of high-level thinking skills based upon advice  
378 and guidance from the instructor [95].

381 We sought to identify the current learning strategies students apply, through the use of questionnaires and observation.  
382 We feel that improving learning skills alongside instruction relating to the field may help students through the liminal  
383 space and conquer the threshold concepts within this domain. To determine the best practices within AI education, we  
384 also felt it was necessary to investigate current practices within computing and data science.

## 387 2.4 Programming and Data Science Education

389 Teachers in computing have previously sought to identify some of the issues faced by students when learning computing  
390 concepts and techniques. Dale [24] posted an online questionnaire for lecturers asking what they determined the most  
391 difficult topic to teach in an introductory computer science course. The research identified four main areas including  
392 problem solving, programming, object-oriented design and lack of student maturity. The difficult nature of learning to  
393 program has also been acknowledged alongside the high dropout rates for such courses [75][71], and is pertinent to  
394 AI education as programming skills are required. Awareness of the importance of student engagement and student  
395 variation requires teachers to be adaptable to meet students’ needs, it is also important to recognise that specific topics  
396 will require longer and greater emphasis than others [76]. This study aims to identify which topics within this domain  
397 will require greater emphasis.

401 2.4.1 *Programming.* Most undergraduate computer science courses include modules that specify a teaching of theory,  
402 the propositional knowledge and practical application of that theory to ensure procedural knowledge [90]. Questioning  
403 and exploration of concepts through computational modelling and programming enables students to increase their  
404 engagement with the theoretical concepts being taught [23]. This is a common pedagogical approach based on  
405 constructivist ideas and active learning [39]. As AI modules are within the computer science domain, we expect AI  
406 courses will follow this practice. However, lack of prior mathematics knowledge needed to comprehend the theoretical  
407 aspects of AI may be exacerbated by the use of programming exercises as students may struggle to identify suitable  
408 models for a specific task or may not understand the architecture of a model and how to program this. Therefore, it is  
409 important for the module leader to identify the level of cohort mathematics skills at the outset of a course. Programming  
410 modules have a number of similarities with AI, including the wide range of abilities and educational backgrounds of  
411 the cohort which can lead to a diverse spectrum of successful and unsuccessful outcomes [75]. In our study, the case  
412 studies from the participating universities enabled identification of cohort diversity relating to prior knowledge and  
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417 confidence and the impact this may have on module outcomes. This is discussed in greater detail in the Results and  
418 Analysis section.

419 There are a number of possible obstacles which can hinder students progressing from novice to expert within  
420 programming including confidence, lack of strategies and mental models [75]. These obstacles can manifest when  
421 students have a lack of social persuasion, such as feedback from influential peers [56] which can boost their self-  
422 efficacy [71], as well as a scarcity of “soft skills” such as goal setting and critical thinking [34]. The potential obstacles  
423 encountered by novice programmers are relevant to all aspects of AI courses due to preconditioned ideas students  
424 may have about the domain and computing and mathematics knowledge from previous courses. For example, logically  
425 verifiable algorithms have been key to the theory of computing practice, however this differs with machine learning as  
426 a typical model is likely abstruse and the verification process “is not a logical proof of correctness” [84].  
427

428 One key strategy which has been employed to aid students within their progression to expert includes the use of  
429 mental models [71]. A mental model invokes a user’s internal representation of components and rules of a system.  
430 There may be variation regarding the completeness of the model as a synonym for the student’s comprehension of the  
431 modelled domain [13]. A student’s mental model can be enhanced through experiential learning tasks [71]. Research has  
432 shown that a student’s mental model influences their level of self-efficacy and this in turn can affect course performance  
433 [71]. Examining student’s preconceptions of machine learning should allow for a clearer understanding of their mental  
434 model and any misconceptions. We investigated this as part of our research questionnaire, further detailed in the  
435 Methodology section.  
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441 *2.4.2 Data Science.* Data science is a similar topic to AI in terms of content, which relates to data processing [11],  
442 although there is an element of ambiguity related to this term and the technical skills that are required. For example,  
443 companies looking to hire a data scientist will often expect the candidate to be competent in AI [1]. Many data  
444 science courses contain principles related to machine learning [36] and may even cover this topic as part of the course  
445 content. From a technical perspective, data scientists “are seen as experts in advanced computational tools, data mining  
446 algorithms, statistical analysis, and machine learning” [1]. Research related to the teaching of data science has shown  
447 that some courses within this subject do not require students to undertake a course pertaining to probability theory,  
448 multivariate calculus, linear algebra or statistics [1], topics which are characteristically associated with introductory AI  
449 courses. This may lead to students having difficulty comprehending the heavy mathematical theory involved in such  
450 courses.  
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452 Recommended practices for teaching a data science course include organising the course around a range of case  
453 studies, writing code live during a lecture and minimisation of the use of mathematical notation and instead, where  
454 possible, using computational approaches such as visualisation [41]. Within the case study, the use of these best practices  
455 will be noted to determine if they are employed when teaching AI.  
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460 *2.4.3 Programming and Data Science Education Key Points.* As AI is often categorized as a form of computing science,  
461 there are a number of inherent similarities within the educational approach, such as a mixture of theoretical and practical  
462 instruction. Potential barriers to high attainment within such courses include the identified difficulty of learning to  
463 program, confidence issues and contention relating to mental models and the influence on self-efficacy. Identified best  
464 practice relating to the teaching of data science include case studies and practical examples. Determining which of  
465 these practices are employed within AI education will help towards the framework for teaching this domain.  
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### 3 METHODOLOGY

As part of this study, we used five different methods for data collection to determine what might constitute best practice in AI education. As part of the best practice framework, we wanted to determine if mathematics anxiety was an issue and potential methods to alleviate this through self-regulation, as well as identify potential threshold concepts within this domain. One of the main limitations of our study was that participation was voluntary which bounded our response from particular data collection methods. Baruch [5] conducted a review into reasonable response rate in academic studies and found that the average response rate for questionnaires was 55%, however they found that in some cases the response rate was as low as 10%.

One of the research methods for this study was online inquiry relating to institutions offering some form of AI course to determine what type of courses were available and what form these courses take. We looked at UK, EU and US institutions who offered courses at HE level as a starting point, with the specific search criteria of entry requirements, module prerequisites and description of module topics. These search criteria were chosen as we were looking to determine prerequisite mathematics knowledge required for such courses as well as specific AI content covered. The systematic search investigated UK universities first, we then covered European and US institutions in a wider search.

#### 3.1 Case Studies

We used case studies at three different universities as a method for this research. We anonymized these as agreed in the research participation form. One of the universities, university A, is part of the Russell Group which are an “association of research-intensive universities” [32]. The other two universities, university B and C are within the top one hundred UK universities guide by The Guardian [91]. The overall aim of the case studies was to comprehend how the subject was taught at that institution and to determine both student and lecturer opinion. The main methods of data collection included semi-structured interviews and questionnaires for the lecturers and questionnaires and the one-minute paper for the students [87]. Observation of lectures was also conducted to collect contextual evidence relating to the student and teacher experience. The aim was to conduct all of the data collection methods at all three universities; however, this was limited by the voluntary nature of the study and the level of data collection permitted at each institution. At university A, the data collected included an interview with the module lead, pre- and post-module questionnaires, observation and the one-minute paper. Data collection differed at the other two universities, the one-minute paper was not completed at either and university C did not use the questionnaires, however semi-structured interviews and observation were completed at both.

#### 3.2 Data Collection Method 1: Online Systematic Review of Modules

To determine the range of AI programmes offered within HE institutions, online information detailing the individual modules covering the topics of AI, machine learning and deep learning was analysed. For clarity, when discussing AI programmes this denotes the overall degree, for example MSc Artificial Intelligence. When detailing specific modules this describes individual courses which comprise the overall degree programme. The search criteria included module pre-requisites, learning outcomes, content, and structure.

The aim of this analysis was to identify core concepts deemed important in an introductory/advanced course and was determined by the reoccurrence of specific themes across all courses. Institutions across the UK, US and Europe were reviewed and specific information recorded included at which level the course was offered (Undergraduate/Postgraduate), whether the course was compulsory or optional, and prerequisites, course content, structure, and the assessment

521 procedure. One of the limitations of this method was the narrow scope of the search, the interdisciplinarity of AI means  
522 that AI is often taught on non-computing courses, such as Business degrees. However, computing departments and the  
523 AI courses they offer were the main focus of this work.

524 The data enabled comprehension of course leaders' determination of the importance of particular topics within  
525 AI due to their presence on the unit specification. Relevance of additional resources was also noted to assess the  
526 popularity of differing modes of information delivery such as preference for online information over textbooks. Due to  
527 the limitations of the study, the institutions partaking in this research have been anonymized.  
528  
529

### 530 3.3 Data Collection Method 2: Semi-Structured Interview

531 We identified module leaders for interview during the online research review. In total, twenty-three lecturers were  
532 contacted with five respondents, a response rate of 21%. The five interviews were conducted with AI lecturers from  
533 differing institutions, three of these universities are part of the Russell Group and the further two are former polytechnics,  
534 considered part of the "post-1992" universities, which transformed UK HE through widening participation [82]. As a  
535 consequence of the response to the call for participants, all interviewees worked in UK universities.  
536  
537

538 The interviews were undertaken in a semi-structured, open-ended style to gain the interviewees' perspective through  
539 how and what questions [10]. Questions (in appendix) referred to the student cohort, module delivery methods, course  
540 prerequisites, module content and topics which they felt students struggled with. All of the interviews were either  
541 conducted in person face-to-face or via video call. This situational organisation allowed for the observation of body  
542 language and the creation of a safe environment where participants could speak freely [97].  
543  
544

545 The interviews were also used to identify the lecturers' perception of key threshold concepts and troublesome  
546 knowledge within the subject domain. This identification is usually the task of the subject instructor and is based on  
547 their experience of teaching in the particular domain of interest [83][25]. Threshold concepts can also be identified  
548 through course participant enquiry, for example, through discipline specific interviews [83].  
549  
550

### 551 3.4 Data Collection Method 3: Questionnaires

552 There were three questionnaires created for this study, one for lecturers who teach some form of AI course and two for  
553 students participating in an AI course. It was important to survey both lecturers and students to gain their perspectives  
554 as "students' perceptions may be doubted in relation to academics' perceptions" [18]. The questionnaire for lecturers  
555 was designed to determine the type of courses they teach relating to AI. Questions covered the course requirements,  
556 prerequisite mathematics and programming skills, course content and resources used for additional learning. The  
557 lecturers were also asked, based upon their experience, which topics students tend to have difficulty with (questionnaire  
558 in appendix). The questionnaires were sent alongside an interview request detailed in section 3.3; however, the response  
559 rate was poor at 13%.  
560  
561

562 Questionnaires designed for students included a preliminary questionnaire for one of the institutions in the case  
563 study, university A, over two separate cohort years, to determine the students' background, their level of mathematics  
564 and programming competency and their overall expectation of achievement level. Getting students to self-report on  
565 their mathematics knowledge and confidence within this domain is one of the key methods in identifying mathematics  
566 anxiety [72]. The second cohort also received a course completion questionnaire to determine their experience in  
567 learning this topic during the twelve-week MSc course.  
568  
569

570 Twenty-one students completed the preliminary questionnaire within the first cohort. Within the second cohort,  
571 thirty-five completed the preliminary questionnaire but only seven completed the post-module questionnaire. The  
572

573 response rate for the post-module questionnaire was lower however, there are a number of possible reasons for this  
574 including optional participation. The preliminary questionnaires were completed on paper within class whereas the  
575 post-module questionnaire was online and was brought to the students' attention around the time of their exam.  
576

577 The questionnaire, designed for completion at the end of the module was identical for all participating universities  
578 (university A and B) apart from the listed course content. The specific topics from the course were catalogued to assist  
579 the students in determining which they found the most challenging and those they were still unsure about. We wanted  
580 to determine how confident the students felt about applying AI after course completion to provide insight into their  
581 experience on the course. Students were also asked which additional resources they used and how useful they found  
582 these. Demographics such as age and gender were also recorded to determine who is undertaking courses in this  
583 domain as well as students' educational background, mathematics and programming experience. There were sixteen  
584 respondents from university B. Links to the questionnaires are contained in the appendix.  
585  
586

### 587 **3.5 Data Collection Method 4: One-Minute Paper**

588  
589 Within the machine learning module at university A, the "one-minute paper" method was employed twice within  
590 the same cohort to gauge how the students were finding the module, (including their perceived difficulty of certain  
591 topics), to aid with the identification of threshold concepts. The one-minute paper is a simple, low-technology technique  
592 for gathering regular feedback from students relating to their learning experiences, by anonymously asking students  
593 simple questions based on their learning experience [17]. The one-minute paper gives students an opportunity to ask  
594 questions which they may have been reluctant to ask within the lecture. Participation in this form of data collection  
595 was higher compared to the questionnaires as students were notified that their responses would determine the content  
596 of the revision session and that questions from the paper would be addressed. Over the two-week period that this  
597 data collection took place, thirty-one students participated out of a class of around fifty. As with all methods of data  
598 collection the one minute paper was optional.  
599

600  
601 One of the potential benefits of the one-minute paper is its capacity to promote student reflection [87]. Due to the  
602 block taught nature of the participating university, which entails shortened, time intensive modules, delivered one at a  
603 time [27], the same student cohort completed the one-minute paper at the end of each week of lectures which were  
604 held over a two-week period. The module was a masters level course and covered content on both machine learning  
605 and deep learning, culminating in a practical project applying a range of the concepts taught.  
606  
607

608 As part of the paper students were asked to mark the topics covered in that week's lectures which they perceived as  
609 the most difficult and to list any subjects which they were still unclear on. To conclude the exercise, students were asked  
610 to rate their confidence in their comprehension of the topics on a scale of one to ten. The confidence scale was included  
611 to comprehend how well the students thought they were understanding and learning the material. The one-minute  
612 paper used can be found in the appendix.  
613  
614

### 615 **3.6 Data Collection Method 5: Observation**

616  
617 Observation, as a research method, has a number of advantages including the "potential to yield more valid or authentic  
618 data than would otherwise be the case with mediated or inferential methods" [19]. Observation can also provide data  
619 on "interactions, processes and behaviours that goes beyond the understanding conveyed in verbal accounts" [74].  
620

621 Observations were completed at the three universities in the case studies, two of the modules observed were  
622 undergraduate courses (university B and C) and one at master's level (university A). Two of the courses were specifically  
623 focused on machine learning (university A and C) and one was an introduction to AI (university B). Overall, thirty  
624

625 sessions were observed, fourteen on the block taught postgraduate module at university A, twelve at university B,  
626 which was a semester long module and four at university C which had an alternate structure of lecture then practical  
627 session. An observation guide was created to structure the sessions to note topics, teaching strategies, the lesson content  
628 and interactions between lecturer and student. Any questions students asked pertaining to the material were noted to  
629 gain insight into any difficulties students were encountering.  
630

## 632 4 RESULTS AND ANALYSIS

633 Analysis of the findings from the five data collection methods enabled insights to be drawn regarding the current  
634 educational offerings pertaining to AI. As the study used mixed research methods, mixed methods data analysis was  
635 used to analyse the findings. The data obtained through the systematic search of online information was analysed  
636 through recurrence of specific themes from the search criteria using descriptive statistics techniques such as frequency  
637 distribution [64]. Both interview and observation data were transcribed, segmented, and coded into categories. Standard-  
638 isation was also used for the interview data to ensure it was comparable. Response frequency and thematic occurrence  
639 was used to identify common AI topics which were perceived as troublesome on both the questionnaires and one-minute  
640 papers. Further details on analysis methods will be discussed below.  
641

### 644 4.1 Online Information Findings

645 As part of this study, we conducted online analysis focusing on the UK, as well as the US and European universities,  
646 which were present on top university lists such as the Complete University Guide [20]. Nine were reviewed in depth,  
647 five of the universities are part of the Russell Group which is a “self-selecting body representing Britain’s foremost  
648 research-led universities” [92], another three of the universities are in the Complete University Guide top fifty UK  
649 university league table for 2022 [20] and one of the universities is a well renowned US institution.  
650

651 From this analysis, modules specific to this domain are offered at both undergraduate and postgraduate levels as both  
652 compulsory and optional modules within a host of degree programmes. Table 1 outlines, to the best of our knowledge,  
653 the current degrees offered by each institution which offer some form of AI module. Some universities, for example  
654 Russell Group #2 and #3 offer interdisciplinary courses such as Computer Science and Philosophy. Students enrolled on  
655 this degree may have differing educational backgrounds which would need to be taken into account when teaching the  
656 more technical material. Table 1 also demonstrates the range and variability of AI modules offered by the universities,  
657 with many also offering specialisations within this field, such as computer vision and robotics.  
658

659 The majority of these modules require a high level of mathematics knowledge, particularly in probability theory,  
660 calculus and linear algebra. All of which are pertinent to cognition of the theory of AI. In some cases, the institution  
661 required a formal mathematics qualification, however, the majority offer refresher sessions on these topics within the  
662 module content. Based upon this initial analysis, some universities do not require knowledge of statistics for admission  
663 onto their AI modules. This omission may lead to some students struggling to grasp some of the theoretical aspects of  
664 AI, due to its mathematical foundation which could have implications on student confidence and mathematics anxiety.  
665

666 Module content depended upon the overarching topic of the module for example, artificial intelligence, machine  
667 learning or deep learning and whether this course was introductory or advanced, taught at undergraduate or postgraduate  
668 level. The majority of courses covered some form of supervised and unsupervised learning and specific models such as  
669 convolutional neural networks and recurrent neural networks. Some universities only list a broad course overview  
670 stating that for instance unsupervised learning will be covered, however some institutions specify individual models  
671 such as recurrent neural networks.  
672  
673  
674  
675  
676

Table 1. Prerequisites related to AI modules offered by the researched institutions

University	Degree Programme	Modules Offered	Module Prerequisites
Russell Group University #1	<b>BSc/MEng:</b> Computer Science, Mathematical Computation, Computational Finance. <b>MSc:</b> Computational Statistics and Machine Learning, Computer Graphics, Vision & Imaging, Data Science and Machine Learning, Machine Learning, Robotics and Computation.	Supervised Learning, Advanced Deep Learning and Reinforcement Learning, Advanced Topics in Machine Learning, Applied Machine Learning, Graphical Models, Introduction to Deep Learning. <b>Level:</b> UG and PG	Basic mathematics, calculus, probability theory, linear algebra, Python coding skills.
Russell Group University #2	<b>All courses BA/Masters:</b> Computer Science, Mathematics and Computer Science, Computer Science and Philosophy.	Machine Learning, Advanced Machine Learning. <b>Level:</b> UG and PG	Linear algebra, calculus, probability theory, continuous mathematics, design and analysis of algorithms, programming skills.
Russell Group University #3	<b>BSc/MEng:</b> Computer Science, Computer Science and Electronics, Computer Science and Mathematics. <b>MSc:</b> Digital Health, Data Science, Financial Technology with Data Science.	Machine Learning, Artificial Intelligence with Logic Programming, Applied Deep Learning. <b>Level:</b> UG and PG	Linear algebra, multivariate calculus.
Russell Group University #4	<b>BEng/MEng:</b> Computing Specialisms: AI and Machine Learning, Visual Computing and Robotics, Management and Finance. <b>MSc:</b> Advanced Computing, AI.	Introduction to Model Based AI, Introduction to Machine Learning, Computer Vision, Mathematics for Machine Learning. <b>Level:</b> UG and PG	Logic and Prolog, essential skills programming and mathematics, linear algebra, statistics.
Russell Group University #5	<b>BSc:</b> Computer Science. <b>MSc:</b> Data Science, Cloud Computing.	Machine Learning <b>Level:</b> PG	None listed.
US University	Computer Science (UG and MS)	Machine Learning. <b>Level:</b> Not listed	Knowledge of basic CS principles, coding skills, probability theory, linear algebra.
Top 50 UK University #1	Computing MA, Computing Science BSc/MEng. <b>MSc:</b> Artificial Intelligence, Data Science.	Grand Challenges of Computing and Artificial Intelligence. <b>Level:</b> UG	None listed.
Top 50 UK University #2	<b>BSc:</b> Artificial Intelligence, Computer Science, Data Science. <b>MSc:</b> Advanced Computer Science.	Introduction to Intelligent Systems, Cognitive Neural Networks. <b>Level:</b> UG	Further Object-Oriented Programming module, A-Level Mathematics or equivalent.
Top 50 UK University #3	<b>BSc:</b> Computer Science Specialisms: Artificial Intelligence. <b>MSc:</b> Computer Science, Advanced Computer Science, Data Science.	Intelligent Systems, Machine Learning and Computer Vision, Artificial Intelligence and Robotics. <b>Level:</b> UG and PG	None listed.

As displayed in Table 2 there is a wide range of variability in content for modules which are offered at similar education levels. The majority of AI modules are either taught in the final undergraduate year or within a postgraduate degree. The modules detailed in Table 2 are the same modules as listed in Table 1. The type of module also determines the complexity of the AI taught, for example more applied modules and introductory courses will not require as much theoretical knowledge as more advanced courses. Russell Group University #4 offers a specific introductory course in machine learning which gives a broad overview of the field and acts as a basis on which students can continue onto more advanced studies. Universities such as Russell Group University #1 and #2 take a more in-depth theoretical approach, particularly at Russell Group University #1 where the focus is on optimisation and the challenges of the various machine learning approaches. This variability between institutions, particularly within modules offered at a similar cohort level (e.g., undergraduate and postgraduate) displays the lack of a discipline specific benchmark necessary to form a coherent educational approach. This is pertinent as AI, machine learning and probabilistic programming are now considered major technologies for inclusion, particularly within UK master's degree programmes [69].

Table 2. Content specific to modules which focus on machine learning

University	Modules Offered	Overview of Content
Russell Group University #1	Applied Machine Learning, Advanced Topics in Machine Learning.	Kernel methods, ICA (Independent Component Analysis), SVM (Support Vector Machine), regularisation, optimisation, classification, regression, clustering.
Russell Group University #2	Machine Learning, Advanced Machine Learning.	Supervised learning, unsupervised learning, Bayesian neural networks, autoencoders, RNN (Recurrent Neural Network), backpropagation, LSTM (Long Short-Term Memory), CNN (Convolutional Neural Network), clustering.
Russell Group University #4	Introduction to Machine Learning.	Decision trees, k-nearest neighbour, regression, neural networks (perceptron, backpropagation).
Russell Group University #4	Machine Learning.	Supervised learning (regression, decision trees, SVM, k-nearest neighbour), unsupervised learning, deep learning (CNN, RNN, LSTM, autoencoders) PCA (Principle Component Analysis).
US University	Machine Learning.	Supervised learning (logistic regression, perceptron, naive Bayes, SVM), unsupervised learning (clustering, k-means, PCA, ICA), deep learning (neural networks, backpropagation).
Top 50 UK University #3	Machine Learning and Computer Vision.	Supervised learning, unsupervised learning, legal and ethical issues in computer vision.

Assessment methods for these courses predominantly involve an exam and coursework. This form of assessment allows instructors to examine both the students theoretical understanding as well as their practical application. Within these modules, the assessment methods often reflect the overall aim of the module, for example, the Applied Machine Learning module, detailed in Table 2 as offered by the Russell Group University #1 employed a formative assessment method of three challenges each weighted at 10% for the overall mark. This choice of coursework in conjunction with summative assessment taking the form of an exam, reflects the modules aim in teaching students how to implement machine learning in practice. The use of both exam and coursework provides an opportunity for students who may have low confidence in their technical skills, predominantly assessed through coursework, or mathematics anxiety related to the theoretical elements of this subject, assessed through the exam, a chance to demonstrate their strengths within these areas. Therefore, the use of mixed assessment methods may be best practice within AI. Most modules consisted of both lectures and practical sessions alongside a reading list to provide further guidance and instruction. These instructional techniques are routine within other computing pedagogies, this will be reviewed in the case studies to determine its prevalence and use within AI modules.

## 4.2 Interview Results

The data collected from the semi structured interviews was first transcribed, then segmented into specific descriptive units, which were “prerequisites”, “pedagogy”, “content” and “perceived difficulties”. These segments were then coded into more specific categories such as “supervised learning” for the “content” category, then similarities and distinctions were determined through frequency analysis. Based upon the interviews undertaken, four of the five instructors taught courses delivered on an undergraduate program. All modules were taught through a mixture of lectures and practical sessions to enable students to comprehend the theory and then undertake practical examples. One of the interviewees advised that they “think students learn better by doing something” and that they “try to make it easy to see an end result” for the practical tasks they set for students, this is an example of implementation of active learning pedagogy [22].

Module content varied depending upon the overarching theme, however all of the courses contained some form of supervised and unsupervised learning and instruction on neural networks, implying that these are essential topics for inclusion on an AI course. 66% of the lecturers stated that students had issues with the theoretical aspects of the course

781 compared to the practical work. The interviewees were questioned on any additional resources they used as part of their  
782 teaching. All respondents stated that they used online resources to supplement material covered within the lectures  
783 and to provide further detail on topics covered. The prevalence of online resources as a learning tool suggests that  
784 this method of instruction provides a useful service to bolster lecture material, the popularity of this method amongst  
785 lecturers may reflect a preference by students for this type of material.  
786  
787

### 788 4.3 Questionnaire Results 789

790 The questionnaires completed by AI lecturers and students participating in the case studies have been analysed through  
791 descriptive statistics and statistical techniques including analysis of variance to determine any differences among the  
792 groups.  
793

794  
795 4.3.1 *Lecturer Questionnaire.* The low response rate to the questionnaire for lecturers teaching AI means that the  
796 results were limited, however they did provide a good indication of the expectations the lecturers have of students, the  
797 type of content they teach and any specific teaching strategies they employ. The majority of the lecturers expected  
798 students to have knowledge of linear algebra, probability theory and familiarity with basic statistics before starting their  
799 module. Results from the frequency analysis indicated that the most commonly taught topics included linear regression,  
800 support vector machines, convolutional neural networks, principal component analysis and Bayesian machine learning.  
801 Respondents also noted that the most common student difficulty was with the mathematical aspects of the module and  
802 identified the importance of real-life examples and practical projects to aid students with their learning.  
803  
804

805  
806 4.3.2 *Pre-Module Student Questionnaire.* The pre-module questionnaire was completed within university A. Participat-  
807 ing in the case study were two differing cohorts of students completing the same module. This postgraduate module in  
808 Machine Learning was block taught and covered both machine learning and deep learning. The majority of students on  
809 the course had a mathematics attainment level of A-Level or equivalent at 37%, with mathematics as a major part of  
810 their undergraduate degree the second most frequent at 26%. The participants were asked to rate their confidence in  
811 their mathematics and programming ability on a scale of one to ten (ten being exceptionally confident), the average  
812 confidence level in mathematics was 6.6 and the average confidence in programming was 6.2. The students were also  
813 asked whether they expected to find the theoretical or practical aspect of the module more difficult, 71% selected  
814 theoretical. The mean confidence level for student's expectation to do well in the module was 6.6.  
815  
816

817 One-way between groups ANOVA, a statistical test to compare the variance between different groups [66], was  
818 carried out to determine if there was a difference in self-reported mathematics confidence for the different groups of  
819 mathematics attainment. These groups included GCSE, A-Level or equivalent, undergraduate degree and specifically  
820 whether this was in Mathematics. There was no significant difference found, however we did find that the higher the  
821 level of mathematics attainment, the higher the self-reported confidence level. This highlights the variation in students  
822 educational background and the impact this can have on student self-efficacy.  
823

824 Determining which learning strategies the students were going to use was important to identify which methods they  
825 thought would aid them with their learning. The most popular learning strategies chosen by the students included note  
826 taking, practical exercises and online guidance. The strategies that the participants expressed they would not use were  
827 more holistic strategies such as reflection, goal setting and self-evaluation. As this was a multiple-choice question there  
828 was no scope to ask the reasoning behind their choice. However, this has potential for a future study pertaining to  
829 perceived efficacy of specific learning strategies.  
830



833 The students were asked to write a brief description of what they thought machine learning was. There were a  
834 range of answers which were categorised into groups such as “Prediction”, “Modelling” and “Classify data.” The most  
835 populated groups were “Learning/extracting knowledge from data”, “Prediction” and the “Other” category. The “Other”  
836 category was composed of answers which did not fit any other group, answers included “it is used quite widely by a lot  
837 of companies” and “a combination of mathematics and programming.”  
838  
839

840 *4.3.3 Post-Module Questionnaire.* There were two post-module questionnaires, one within the Russell Group university  
841 A, Machine Learning postgraduate module and the other at the post 1992 university B undergraduate Artificial  
842 Intelligence module. Both of the questionnaires were identical apart from content listed for the question asking students  
843 which topics they found the most challenging.  
844

845 The majority of the students from the undergraduate module (university B) had a mathematics attainment level  
846 of GCSE or equivalent at 50%, with the second highest being A-Level or equivalent at 31%. The level of mathematics  
847 confidence was much more evenly spread than the other university, however none of the participants rated their  
848 confidence below a 5. 56% of students found the practical aspects of the module more difficult than the theoretical. The  
849 participants identified the most challenging topics as knowledge representation, search algorithms, k-means algorithm,  
850 artificial neural networks, multi-layer perceptron and backpropagation. The participants identified their most useful  
851 study strategies as note taking and practical exercises, however they also listed more holistic approaches such as goal  
852 setting and reflection.  
853  
854

855 Within the Russell Group university (university A), the participants of the questionnaire were the same students who  
856 completed the preliminary questionnaire. The participants identified the most challenging topics as backpropagation,  
857 supervised and unsupervised models and deep learning. Supervised and unsupervised models and deep learning are  
858 both broad categories which would require further investigation to determine specific issues within these domains.  
859 There was an even spread between respondents who thought mathematics was challenging and respondents who didn’t  
860 find mathematics difficult, this may reflect the variety of mathematics educational background within this cohort. The  
861 participants identified note taking and practical exercises as the most useful learning strategies.  
862  
863

864 *4.3.4 One-Minute Paper Results.* The one-minute paper was completed by one of the cohorts from university A, the  
865 same group of students completed both rounds of the paper. Q1: Which topic(s) did you find the most difficult this week  
866 and Q2: Which topic are you still unsure on, required frequency analysis to determine any unifying concepts which the  
867 students identified as troublesome. Content analysis was achieved on the specific question’s students asked through  
868 open coding, categorisation and frequency of occurrence [19].  
869  
870

871 The postgraduate Machine Learning module was block taught, lasting a duration of three weeks. Participation in  
872 the one-minute paper was optional and students were asked to complete it after each week of the taught material.  
873 The exercise was not conducted in the third week as this consisted of guest lectures which were not assessed. The  
874 most frequent responses to Q1 were the support vector machine and the multilayer perceptron. The main topics which  
875 students were still unsure on were the convolutional neural network and the recurrent neural network with 22% each,  
876 making up nearly half of the overall responses.  
877

878 There were two common themes that emerged from Q3: Any specific questions? There was confusion with the  
879 backpropagation algorithm and the students were unsure on feature engineering. 57% of respondents mentioned these  
880 two topics. Students also used this question to request further practical examples within lectures. The average confidence  
881 level in what they had learnt that week was 5.1 in the first week and rose to 6.8 in the second week, although there  
882 was a variation in the confidence levels with some students rating their confidence very low. As the confidence level  
883  
884

885 pertained to the topics covered in each week, this rise may reflect the students finding the second week’s content easier  
886 or the students may have gained more confidence overall within this domain. However, due to the low sample size,  
887 specific causations cannot be determined.  
888

889 *4.3.5 Observation Findings.* As a standardised observation guide was used during observation sessions, this ensured  
890 that the results were more easily comparable. The data collected during the observation sessions was first transcribed,  
891 then content analysis was applied. Content analysis methods included category creation, coding of the content from  
892 the transcribed observation guides, logging of frequent occurrences of categories and finally interpretation of results.  
893

894 Within the three institutions participating in the case studies, observation took place in two undergraduate modules  
895 and a master’s module. The content on the courses differed due to the educational level and learning outcomes, however  
896 common topics between the three modules included decision trees, support vector machines and the k-means algorithm.  
897 Two of the courses did refresher mathematics sessions and covered deep learning. Interspersed within the lectures for  
898 all of the modules were practical real-life examples, the lecturers of each course also discussed their research within the  
899 field which appeared to further engage the students.  
900

901 The amount of student and lecturer interaction was varied amongst the institutions with interaction being at a  
902 minimum within some lectures. At university B, students were given a group task within each lecture which enabled  
903 active learning and appeared to increase student engagement as the students expected to be questioned on the content.  
904 This teaching method also furthered interaction between the lecturer and students as the learners were more forthcoming  
905 with questions on concepts which they did not understand.  
906

907 The number of students attending each lecture varied per session, university A had the highest average attendance at  
908 95%, however attendance tailed off during the week of guest lectures. University C was a much smaller class of around  
909 fifteen students, however attendance was fairly consistent across all sessions. University B had consistent attendance of  
910 around thirty-five students which was an average attendance of 58%.  
911

912 Specific questions that students asked during the lectures often pertained to the merits of choosing specific models  
913 over others, for example one student asked, “what is the advantage of the support vector machine over logistic  
914 regression?” Other questions related to mathematical notation and the backpropagation algorithm.  
915

## 916 5 SUMMARY OF PRELIMINARY FINDINGS

### 917 5.1 Mathematics Anxiety and Educational Background

918 Based upon analysis of the online information, interviews and questionnaires with the lecturers, some AI modules  
919 require a formal mathematics qualification or in-depth knowledge of mathematics topics pertinent to AI. Some of  
920 the modules offer booster sessions, however a lack of uniformity in prerequisites may lead to a disparity in students’  
921 understanding of theoretical issues within AI and a lack of preparedness amongst the cohort of students. For example,  
922 two of the institutions listed in the top 50 UK universities [20] do not list any prerequisites for undertaking their AI  
923 based courses. However, the type of modules they offer, such as Machine Learning, and Computer Vision cover topics  
924 which require a mathematical basis to fully understand the content. Offering AI as an interdisciplinary course will also  
925 have implications relating to pre-requisites and technical skills. One lecturer who was interviewed stated that they “can  
926 tell students come from different backgrounds” and that some students struggle with the terminology and applying  
927 their previous knowledge to a new topic.  
928

929 Within the interviews and questionnaires with the lecturers, a consensus was reached that the mathematical aspects  
930 of the module are where students encounter the most difficulty. However, within the questionnaires completed by  
931

937 students in the case studies, average self-reported confidence in mathematics was above a five for all participating  
938 institutions. This may be due to a reluctance to admit low confidence in mathematics skills at this educational level.  
939 There was some disparity in mathematics attainment level for the two universities who completed the questionnaires,  
940 within the postgraduate module (university A) the majority of students had an A-Level in mathematics. However, on  
941 the undergraduate module (university B) the majority of students had achieved GCSE level mathematics. Within the  
942 UK education system, GCSE qualifications are level 1 and 2 depending on grade achieved, A-Levels are level 3, an  
943 undergraduate degree is level 6 and master's degree level is level 7 [33].  
944

945 Although students on the postgraduate module had a high-level of mathematics attainment and the average level  
946 of mathematics confidence was 6.6, 71% of the students expected to find the theoretical side of the module more  
947 complex than the practical aspects. This correlates with the findings from the lecturer interviews which supported  
948 the claim that students have greater difficulty comprehending the theory of AI. However, the majority of students  
949 on the undergraduate module found the practical aspects more difficult than the theory. One interesting finding and  
950 possible explanation in the disparity between the students on the postgraduate module mathematics confidence level  
951 and expectation to find the theory more difficult is that the students lack self-regulation and metacognition skills. The  
952 students on the undergraduate module reported their use of more holistic learning strategies such as goal setting and  
953 reflection, however the students on the postgraduate module did not use such techniques.  
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## 957 5.2 Threshold Concepts

958 Identification of the threshold concepts within the area of AI and creation of a domain framework will give lecturers  
959 understanding of the topics within this domain which are considered core knowledge and may be a source of difficulty  
960 for students. There were two strands towards identifying the threshold concepts, these were, 1. topics deemed essential  
961 to teach as identified through the online analysis, interviews and questionnaires with the lecturers and 2. topics the  
962 students had difficulty with, identified through observation, interviews and student questionnaires.  
963

964 The most frequently taught topics within the AI modules in the case studies included decision trees, support vector  
965 machine, k-means algorithm and specific deep learning models such as convolutional neural networks and recurrent  
966 neural networks. The online analysis showed a wide range of topics which are covered within the AI domain, from  
967 specific applications of AI such as computer vision, to introductory machine learning modules. However, nearly all of  
968 the modules contained content relating to supervised and unsupervised models and some form of deep learning.  
969

970 The topics students most frequently identified as challenging were mainly related to deep learning, particularly  
971 multi-layer perceptrons, convolutional neural networks, recurrent neural networks and the backpropagation algorithm.  
972 Lecturers in this domain also highlighted clustering as a pivotal topic which corresponded with the student response  
973 that they had difficulty particularly with the k-means algorithm.  
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## 978 5.3 Pedagogies and Best Practice

979 Consistent with other areas of computing education, the use of problem based learning and practical examples are seen  
980 by both lecturers and students as an effective learning method for AI. Alongside practical examples, the use of real-life  
981 examples were highlighted by lecturers in the questionnaires, interviews and observations. The use of these methods  
982 not only contextualises the theoretical knowledge within the applied context but also appeared to increase engagement.  
983 The lecturers in all of the observed modules also took time to discuss their research within the AI domain which seemed  
984 to further immerse the students in their learning. Within AI modules there seems a greater importance in the use of  
985 practical, real-life examples as opposed to traditional computing courses. One of the possible explanations for this is  
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989 the amount of content that can be covered on these types of courses, two of the lecturers interviewed mentioned that  
990 students often complain about the amount of content covered. Assimilating the different learning algorithms taught  
991 into a practical context, for example deciding which model to use has shown to be an issue for the students as identified  
992 by the student questions on the one-minute paper.  
993

994 The assessment procedure for these types of courses, identified through the online analysis and interviews, detail  
995 that a mix of exams and coursework is the most common form of assessment. The pedagogical foundation for this  
996 assessment methodology is that exams test the student's theoretical understanding, and the coursework determines  
997 the student's practical execution of the topics learnt. For students to more readily associate the theoretical aspects  
998 of this domain to their practical application there is a need to include more formative work within these types of  
999 courses. For example, through supplementary material which students can work through independently to gauge their  
1000 understanding of concepts, this may also increase student self-efficacy and consequently enable them to become more  
1001 self-regulated.  
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1004 Preliminary results from the data analysis suggests that in the modules covered by our study, lecturers often referred  
1005 students to additional online resources for further information. This supports earlier research where it was found  
1006 that students are not using textbooks as often and are turning to the internet instead [7]. The shortfall in consistency  
1007 relating to course prerequisites, specifically mathematics knowledge and the apparent lack of student confidence and  
1008 capability relating to the theory of AI suggests that both students and lecturers may benefit from an AI online learning  
1009 tool to supplement module content.  
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## 1013 6 DISCUSSION

### 1014 6.1 Teaching Strategies

1015  
1016 One of the most important issues pertinent to any educational context is awareness of student engagement levels and  
1017 the variation of skills and contextual knowledge students possess. It is a valuable skill that lecturers are adaptable within  
1018 their learning methods to meet the varying student requirements. Aligning with threshold concepts and recognising that  
1019 some topics will require a longer time to be spent ensuring the students understand these topics is particularly relevant  
1020 within the field of AI as there are a number of foundation issues such as feature engineering and backpropagation  
1021 which are often difficult to understand. These topics are essential to understand in order to build a machine learning  
1022 model and were identified as topics students had difficulty understanding. One possible method to engage the learners  
1023 and help overcome threshold concepts is the use of practical, real-life examples. For example, deep learning, especially  
1024 models centered around artificial neural networks were identified as a potential threshold concept, one possible method  
1025 to help students build a better mental model of this concept is by comparing the artificial neural network to human  
1026 learning and neural networks in the brain. Students are often engaged and enthusiastic about learning about themselves  
1027 and this correlation will help them to build a stronger mental model of deep learning. However, it is essential to indicate  
1028 that this mapping isn't exact to avoid further confusion. A lack of a clear mental model can cause anxiety and low  
1029 self-efficacy in the student's belief that they can achieve within their module. Students may not have an effective model  
1030 and may be "susceptible to the fiction that ML has a "hidden mind" [29], therefore it is of particular importance within  
1031 AI modules to clearly define key concepts.  
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1036 There was some disparity between the two universities (A and B) which participated in the questionnaires with  
1037 regard to which aspect of their module they expected or found the hardest. The students on the postgraduate module  
1038 who had the higher mathematics attainment expected the theory to be more complex to learn. However, the students  
1039

1041 on the undergraduate module experienced more difficulty with the practical elements, although this module was not as  
1042 mathematically intensive. As evidenced by the online analysis, there is a wide variety of modules offered within the  
1043 AI domain, with some offering more applied content and others focusing on the theory of a particular sub-discipline  
1044 such as deep learning. The lack of uniformity regarding course prerequisites and variety of educational backgrounds  
1045 may lead to difficulty for students within either the practical or theoretical aspects of the module. Therefore, it may  
1046 be worthwhile offering refresher sessions or supplementary material for mathematics and programming to eliminate  
1047 any disparity in knowledge levels as well as increase student self-efficacy in their ability to comprehend the more  
1048 challenging aspects of the module.  
1049  
1050

1051 A beneficial technique to scaffold engagement in lectures, recognised as part of the observations is the use of group  
1052 activities. Group activities have been shown to increase student motivation as well as offering the students a perceived  
1053 support system which is often not felt when working individually [60][52]. Initiating the lecture by giving an overview  
1054 of the session structure and alerting the students to the fact that there will be an activity, led to students paying greater  
1055 attention and engaging more with the content. It also fostered a more dynamic and open relationship not only between  
1056 peers, but also between peers and the lecturer. As a consequence, there was a marked difference between the number of  
1057 questions the students asked the lecturer in one institution as opposed to the other institutions observed.  
1058  
1059

## 1060 6.2 Mathematics Anxiety and Self-Efficacy

1062 The results from the study, in particular the student questionnaire indicated the students felt somewhat confident  
1063 in their mathematics ability. However, the Russell Group cohort of students (university A) overwhelmingly stated  
1064 that they thought they would struggle the most with the theoretical aspect of AI which is intrinsically linked with  
1065 mathematics. The variability in students' educational background, both societal and educational, may impact upon  
1066 their ability to employ appropriate learning strategies to overcome these difficulties with the theoretical material, for  
1067 example by linking their previous learning with the new material. If students have low self-efficacy, they may not  
1068 have the emotional capability to persist when in the liminal state of a threshold concept. Equipping students with  
1069 metacognitive skills and training them to become more self-regulated learners may help build up student resilience  
1070 when encountering challenging educational scenarios.  
1071  
1072

1073 Potential strategies to alleviate mathematics anxiety and to boost student's self-efficacy includes retesting and  
1074 offering refresher sessions within an AI course to try and balance the inequality of knowledge. Offering retesting within  
1075 a course can benefit the students in a number of ways as the initial test result works as a form of feedback for the  
1076 students. A successful experience within a test can counteract the feeling of failure experienced in the past, it can  
1077 also act as a psychological safety net for students who experience exam anxiety [50] which has also been linked to  
1078 mathematics anxiety [3]. The results from the online analysis indicated that a significant percentage of AI courses use  
1079 exams as a form of assessment, offering retesting or low stakes tests throughout the course may ease student anxiety  
1080 pertaining to this form of assessment, as well as boosting student's self-efficacy by gaining feedback on their progress.  
1081  
1082

1083 Distance learning has also been shown to benefit student anxiety in relation to mathematics [89]. The concept of  
1084 distance learning and online learning are often used synonymously, technological advances have updated distance  
1085 learning methods to provide access to greater educational provision [62]. The findings from both the interviews  
1086 with AI lecturers and the student questionnaire indicate that online resources are a popular learning tool within this  
1087 domain. Creation of an online tool incorporating mathematics knowledge specific to AI and incorporation of different  
1088 metacognition and self-efficacy strategies may help students to ultimately become more self-regulated and to aid their  
1089 anxiety relating to mathematics and the theory of AI.  
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### 1093 **6.3 Confidence**

1094 Students' confidence and their ability to reflect accurately on their own learning are important skills in academia as it  
1095 allows greater control over learning. Equipping students with strategies to reflect and self-regulate is often not a priority  
1096 on academic courses due to time constraints, however, it has been shown that interventions focused on equipping  
1097 students with learning strategies have improved assessment outcomes [38].  
1098

1099 The use of the one-minute paper was to encourage the students to reflect upon their experiences within the course  
1100 and to enable them to express their concerns regarding specific content. The one-minute paper was employed on a  
1101 block taught module, this type of format is more intensive than a traditional layout with teaching taking place over a  
1102 shorter timescale, for example over one semester. The one-minute paper was particularly appropriate for this teaching  
1103 style due to the intensity and fast pace of instruction. The one-minute paper may be a particularly relevant strategy  
1104 for AI courses due to the concerns expressed by the students that these modules are too fast paced and cover a lot of  
1105 material. The one-minute paper can be used to not only engage the students in reflection, but to also alert the lecturer  
1106 to any topics the students are struggling with.  
1107

1108 Another possible method of bolstering student confidence is through the use of sequential tasks which increase in  
1109 difficulty over a period of time. This would enable the student to gain positive experiences within the AI domain instead  
1110 of starting at a high complexity level which almost immediately causes the student to doubt their ability. However, a  
1111 balance needs to be struck with the complexity level to ensure that some higher-achieving students are not deterred  
1112 from continuing in their studies if they feel the material is "too easy". This is especially pertinent in AI courses due to  
1113 cohort diversity. One method of improving student confidence based upon the findings from the observations is to create  
1114 an open and supportive educational environment. This approach enabled students to freely ask questions throughout  
1115 their learning session, expressing aspects of the material which they did not understand and sharing knowledge with  
1116 their peers.  
1117

### 1123 **6.4 Threshold Concepts**

1124 Rountree [76] describes the role of threshold concepts as providing a "model for academics in higher education to  
1125 develop their teaching and support learning." Identification of these concepts within AI will increase lecturers' awareness  
1126 of the specific aspects of this field that students may encounter difficulties with, and they can then plan and implement  
1127 learning strategies to aid with the students' understanding. Due to the limitations of the data collection in regard to  
1128 response rate and narrow selection of institutions and modules, the potential threshold concepts identified in this study  
1129 will require further research to bolster these findings. However, these findings have contributed towards a framework  
1130 for teaching AI as topics to be aware of which may cause students difficulty.  
1131

1132 The results from this research indicate that deep learning is an area that students are either encountering issues with  
1133 or is seen as an important topic which requires greater instruction time. For example, three out of the five lecturers  
1134 who were interviewed taught deep learning within their course and within the one-minute paper, students specifically  
1135 mentioned the recurrent neural network and multi-layer perceptron as being the most testing to comprehend. Further  
1136 research is needed to discover exactly what the issue is surrounding these models. However, both of these models are  
1137 neural networks which may indicate a wider issue with comprehension of this architecture. Students also mentioned  
1138 difficulty with the backpropagation algorithm within the one-minute paper, which is also intrinsic to neural networks.  
1139 Based upon the observation sessions, neural networks are currently being taught in the same manner as other concepts  
1140

1145 in AI. The findings from this study indicate that concepts relating to neural networks may be proving difficult and that  
1146 this topic may need different learning methods.  
1147

## 1148 **6.5 Towards a Framework for Teaching AI** 1149

1150 Working towards a framework for teaching AI requires identification of the threshold concepts, barriers the students  
1151 may face in their learning, issues lecturers face and establishing the best practices in pedagogy. This paper initiates the  
1152 process of creation of the framework, however, iteration of the data collection at a wider scale and with inclusion of  
1153 more diverse institutions will be required to fully deliver the framework.  
1154

1155 The initial outline of the framework, as identified in this paper, starts with the prerequisites for undertaking a  
1156 module in AI. Depending on the type of module and learning outcomes, prerequisites are often listed, however, due  
1157 to the variability in educational backgrounds it is good practice to offer either revision sessions on mathematics or  
1158 programming and to provide supplementary material. The refresher sessions may also help to alleviate any anxiety  
1159 the students have in either their mathematics and technical skills, providing the supplementary material as a distance  
1160 learning opportunity, with the use of low stakes questioning with optional retesting may also improve the student's  
1161 self-efficacy and allow them to build confidence in their skills.  
1162

1163 The main threshold concepts identified within this study were within the domain of deep learning, particularly  
1164 convolutional and recurrent neural networks, multilayer perceptrons and backpropagation. It is important for lecturers  
1165 to align their teaching strategies with some of the difficulties the students may face when learning the threshold  
1166 concepts. Some of the best practices for teaching AI identified in this study include the use of practical examples and  
1167 problem-based learning to embed and contextualize the theoretical knowledge. The use of real-life examples is also  
1168 important to help the students build an appropriate mental model, for example by associating artificial neural networks  
1169 with the human brain.  
1170

1171 Alongside the AI content it is useful to incorporate activities for reflection and self-regulation to assist the students  
1172 in their learning and to improve their metacognition. Potential activities include the use of group exercises, this will  
1173 also help foster relationships between the lecturer and students as well as increase engagement within the lectures. The  
1174 use of the one-minute paper within this study revealed its value and versatility as a method for the lecturer to monitor  
1175 progress as well as helping the students to reflect on any difficulties they are encountering.  
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## 1179 **7 FUTURE WORK** 1180

1181 This analysis of the AI education domain has enabled insight into some of the difficulties both students and lecturers  
1182 can encounter within this field. As with any research project there are limitations, many of the limitations of this study  
1183 centre around low response rate and proliferation of similar types of universities both within the case studies and the  
1184 online systematic review of modules, as only a snapshot of universities were analysed. We may have missed courses  
1185 which did cover some form of AI as we did not have access to all of the course material and the lecturer may be teaching  
1186 aspects of this domain without explicitly stating this in the syllabus. However, this study has led to a basis for further  
1187 research and some ideas for implementing possible solutions to the issues raised by both lecturers and students. Some  
1188 of these possible solutions will be trialed within a new Deep Learning module currently being developed.  
1189

1190 Repetition of the online review of modules with both a wider scope of universities and geographical area will enable  
1191 further insight into the type of AI courses being offered. Alongside this review, the questionnaire for lecturers will also  
1192 be sent with the aim to recruit more participants for both the questionnaires and as potential case studies. Iteration of  
1193 the data collection methods for students within differing cohorts will enable further analysis of the barriers students  
1194  
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1196

1197 encounter when undertaking education within this area. The further research will enable greater investigation into the  
1198 best practices and provide more data and insights for the framework, including conformation of the threshold concepts  
1199 in AI.  
1200

## 1201 8 CONCLUSION

1202 The growing interest in AI related courses at HE level, juxtaposed with the shortage of skilled individuals to fill the  
1203 increasing number of posts within this sector necessitates research into the educational provision within this field. This  
1204 article has explored many facets of educational difficulties and has proposed a number of strategies to help mitigate  
1205 these issues. The aim of this paper was to identify potential best practices and to initiate the creation of a framework for  
1206 teaching AI. Some of the best practices identified through this study include the necessity to outline clear prerequisites,  
1207 specifically related to the module content and learning outcomes. However, the use of prerequisites will not eliminate  
1208 the variation in student educational background, therefore offering refresher sessions is important to attempt to align  
1209 knowledge, particularly in mathematics and programming. Alongside the differences in student educational background,  
1210 students may also experience a lack of confidence in particular aspects of the module, for example, the Russell Group  
1211 university which participated in the case study had the highest level of mathematics attainment, however the majority  
1212 of students expected to struggle with the theory of machine learning. One identified strategy to improve student  
1213 confidence is through the use of supplementary material, particularly resources which offer students the opportunity to  
1214 improve their self-efficacy, for example through reflection.  
1215

1216 One of the teaching strategies which was highlighted as useful by both the lecturers and students was the use  
1217 of practical and real-life examples to help the students build a mental model and embed the theory within a usable,  
1218 practical context. Practical examples are prevalent throughout computing education; however, we feel they have higher  
1219 importance in building the students mental model within the AI domain. This is due to the inherent differences between  
1220 AI and other computing domains, where the majority of students will have experience. For example, in traditional  
1221 programming the programmer creates the steps detailing how to achieve the outcome, whereas in machine learning  
1222 the programmer defines the objective “that the system is trying to maximise” [84] and the verification task “is not a  
1223 proof of logical correctness, but rather a statistical demonstration of effectiveness” [84]. These concepts can be alien  
1224 and difficult to grasp for students who have experience within other computing domains, which as we have seen from  
1225 the online review that AI modules are mainly offered as part of computing degree programmes.  
1226

1227 In conjunction with the identification of barriers to student learning, determining the threshold concepts within this  
1228 domain was also an important step towards the framework. Our main criteria for the threshold concepts were topics  
1229 which were core to comprehending the domain and topics which both students and lecturers identified as difficult. The  
1230 core topics identified pertained to supervised and unsupervised learning, specifically models such as decision trees, the  
1231 support vector machine and the k-means algorithm. The majority of courses also covered some form of deep learning,  
1232 specifically artificial neural networks. There was some overlap between topics deemed essential to teach and topics  
1233 which students had difficulty learning, including the support vector machine and the k-means algorithm. Identification  
1234 of these topics is the first step towards creating a clearly defined set of threshold concepts, which will require further  
1235 iterations of this study with a more diverse set of participants.  
1236

1237 This study contributes to a limited pool of research pertaining to AI education. We sought to provide guidance  
1238 on pedagogical strategies to lecturers within this field and further the understanding of the difficulties faced when  
1239 undertaking education within this domain with the aim of improving student experience.  
1240



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## 1430 A APPENDICES

### 1431 A.1 Link to the student questionnaire

1432 The link is to the questionnaire the students were asked to complete on completion of their Machine Learning module  
1433 at university A: <https://doi.org/10.25405/data.ncl.16587017.v1>.  
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### 1436 A.2 Link to the lecturer questionnaire

1437 The link is to the questionnaire sent to lecturers who teach some form of AI course: [https://doi.org/10.25405/data.ncl.](https://doi.org/10.25405/data.ncl.16587020.v1)  
1438 [16587020.v1](https://doi.org/10.25405/data.ncl.16587020.v1)  
1439  
1440

### 1441 A.3 One-Minute Paper

1442 The link below is for the one-minute paper for week one of the Machine Learning module at university A: <https://doi.org/10.25405/data.ncl.16587038.v1>  
1443  
1444  
1445

### 1446 A.4 Interview Questions

1447 The link below contains the questions for the semi-structured interviews with the lecturers: [https://doi.org/10.25405/](https://doi.org/10.25405/data.ncl.16587071.v1)  
1448 [data.ncl.16587071.v1](https://doi.org/10.25405/data.ncl.16587071.v1)  
1449  
1450