



Pragmatic AI in education and its role in mathematics learning and teaching

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Pragmatic, scalable and sustainable responses to persistent socio-emotional issues such as mathematics anxiety remain elusive. Artificial intelligence (AI) offers a promising approach by enhancing students' perceptions of competence, control, and value while transforming teacher-student interactions. This paper advocates for a research agenda exploring AI's role in shaping achievement emotions and calls for a broader shift in educational research toward leveraging AI for meaningful and transformative learning experiences.

We offer here a call-to-action for researchers and educators as they respond to the ever-growing presence of various implementations of Artificial Intelligence (AI) in our schools and universities. We make this call based on our critique of the dominant discourses around AI in the year following the release of ChatGPT; that is, the discussion has been too focussed on the *products* of education—the lesson plan, the essay, the multi-media presentation—and not sufficiently on the *processes* of learning.

The distinction we make between the products of education and the processes of learning can be a fine one but, in the context of considering the role of AI in education, it should not be understated. When we talk about the use of a technology such as AI, it can be very easy to think in very linear and business-like terms with respect to the efficient production of the things we have traditionally used to signify learning. It can be even easier to forget that those things have been used as signifiers and not as the actual *object* of education. In short, the purpose of education is not to produce artefacts such as essays. Rather, the essay is a tool we use with the objective of transforming the understanding of the student.

These concerns take on new urgency in the context of AI's expanding role in education. The term AI has been in use for nearly 75 years since Turing¹ posed the question, 'Can machines think?' Over the decades, progress in the field has fluctuated, moving through various stages of artificial intelligence and towards the aspirational goals of artificial general intelligence and artificial superintelligence². At the heart of these evolving conceptions of AI is the idea of machines "behaving in ways that would be called intelligent if a human were so behaving³." While contemporary AI systems are undeniably sophisticated, we argue that they are not yet truly intelligent in the human sense. This said, we do not dismiss the possibility of future developments in general artificial intelligence. For the purposes of this article, we intentionally adopt a broad

definition of AI, one that avoids a purely technocentric perspective and instead keeps open the question of how these tools might be meaningfully integrated into the learning process.

With this distinctly *educational* purpose in mind, we seek to use this short article to promote an agenda of educational research and implementation that gives consideration to the use of AI as a means to support student learning in the deeper sense of achieving significant developmental transformations. By way of example, our focus here will be on potential roles for AI in cultivating students' socio-emotional learning (SEL), and we will give particular attention to the persistent problem of mathematics anxiety (maths anxiety). The paper will begin with a short outline of this *educational* ambition, before turning to a discussion of potential AI use cases that might address it.

Managing mathematics anxiety: a socio-emotional learning goal

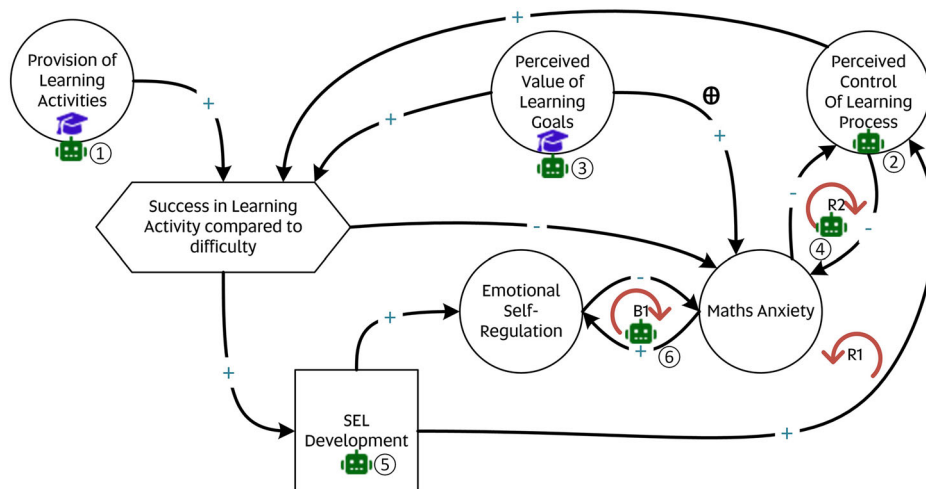
The desire to reduce students' maths anxiety provides an instructive example of how our research and design focus can, if we consider the role of AI, move from the products that represent learning to the underlying educational goals. In the context of mathematics education, SEL can play a crucial role in reducing mathematics anxiety, as it provides students with the emotional and cognitive resources needed to regulate and balance the challenges of learning mathematics.

Maths anxiety remains a significant challenge in schools worldwide. Maths anxiety is an emotional response characterised by a sense of fear, tension, and apprehension when it comes to mathematical tasks and tests⁴. For many students, this anxiety can be so paralysing that it hinders their mathematical learning and performance. While it is normal to feel some level of anxiety when encountering challenging subjects, excessive maths anxiety can lead to avoidance, reduced self-confidence and reduced feelings of control, and even long-term aversion to mathematical learning⁵. Maths anxiety is not confined to the school classroom and has been found to be prevalent across the adult population⁶, often manifesting early in middle school students⁷.

In essence, maths anxiety appears when the subjective appraisal of a student's control over a situation involving mathematics is uncertain and the focus of thoughts revolves around the anticipation and fear of failure⁸. According to the Control-Value Theory of Achievement Emotions, anxiety in educational contexts can be understood as the feeling that arises when students place value on a subject like mathematics but perceive a lack of control over their performance in it⁹. When they value the subject but feel uncertain about their abilities, maths anxiety tends to emerge¹⁰.

Figure 1 presents a much simplified and sharply focussed model of the process of learning mathematics. In this model we suppose that the underlying educational goal in having students successfully complete the mathematics activities (the hexagon) is the development of students' SEL (the square). That is, the activity is a 'means', it is not the 'ends'. Key to this is the provision of educationally appropriate learning activities ①. Also

Fig. 1 | A conceptual model of the process of learning to cultivate students' socio-emotional learning. Arrows indicate the theorised effect of one node on another. Arrows with a '+' indicate a proportional relationship between two nodes while a '-' indicates an inverse relationship. 🏠 indicates nodes where a teacher has significant influence on the process of learning while 🤖 indicates the potential for the use of AI. Loops may be balancing (B) or reinforcing (R). Numbers in circles e.g., ① are references to Table 1.



contributing to an increased likelihood of success in these activities is a student's own appraisal of the control ② and value ③ they have over the process with which they engage with these activities. The teacher is able to take various actions, such as tailoring the relevance of the activity for the student, to cause an increase in the perceived value of the learning and thus increase the likelihood of success. However, an unintended consequence of this action might be a corresponding increase in maths anxiety ④. A student may be able to use their emotional self-regulation to dampen (indicated by the balancing loop B1) this change in maths anxiety, or their appraisal of an increased level of control of their learning may result in a reduction in maths anxiety (indicated by ⊕).

Two reinforcing loops exist in this model. R1 indicates that success in the learning activity can lead to improvements in the underlying educational goal of SEL development. In turn, this leads to greater perception of control in learning activities leading to an increased likelihood of success in future activities. Secondly, R2 shows that an increased perception of control leads to a reduction in maths anxiety which in turn leads to further increases in the perception of control. However, it must be noted that while these reinforcing loops can be helpful in increasing a student's perception of control, they can also have undesirable consequences. For example, R2 also indicates that a perceived loss of control can result in an increase in maths anxiety which then leads to further reductions in perceived control. It is important to stress that the model presented here is not intended to be complete representation of the process of learning. Rather it serves to highlight that effectively addressing the complex issues around students' emotions and learning outcomes requires new thinking, and in this pursuit, AI emerges as a valuable ally.

The provision of highly tailored, high quality learning activities, facilitated by the teacher (as indicated by the mortarboard icon), plays an important role in ensuring that students experience greater frequency of success than difficulty in their learning. Of course, we also need to recognise the value of productive struggle in reshaping students' self-perceptions and fostering resilience. Research highlights the importance of allowing students to engage in tasks that are appropriately challenging^{11,12}. Overcoming difficulty, rather than succeeding solely because tasks are perceived as "easy", can provide students with a sense of accomplishment, and build their confidence. It is also essential to recognise that a highly trained expert teacher who knows their students and how they learn, is invariably the best placed individual to make these assessments. However, the realities of a

classroom environment where one teacher may be working with thirty students, means that there is very little time in a 1-h lesson for this individual assessment to occur. AI systems, that can process multiple streams of complicated information in parallel, can start to address this issue by identifying moments when students are ready to tackle more complex challenges and take action either directly or indirectly through the teacher.

Importantly, we acknowledge that individualised reference points for autonomy and self-regulated learning (SRL) may be beneficial in impacting how students engage with processes like those described in Fig. 1. It is evident that not all students will benefit equally from the same SRL-focused intervention, and this may be particularly true for those students who may initially struggle with self-directed learning. It is equally evident that students will each respond differently to any feedback provided and thus each student will need their own tailored mix of information¹³. The CVT takes into account the role of individual appraisals in shaping emotional responses, acknowledging that students' perceptions of control and value can vary significantly across individuals and situations. From a measurement perspective this implies that absolute measurements of these constructs may not be helpful and that relative measurements of how these change over time may be more informative. This level of fine granularity in students' starting points, is difficult for a single teacher with limited resources to achieve in reality and might lead to the idea of 'teaching to the middle' rather than teaching to the individual. However, this highly pattern-based approach to measurement is ideally suited to a machine based (AI) solution. It also highlights the need for *adaptive* systems that can differentiate between students based on their unique profile and tailor interventions accordingly. AI has the potential to revolutionise this space by monitoring individual learning patterns over time and offering personalised learning experiences¹⁴ with finer granularity than a human teacher can achieve alone. Furthermore, by keeping educators in the feedback loop they will be able to identify which students may require more structured guidance and which students are ready for more autonomous tasks and thus the face-to-face teacher-student dynamic will change.

Designing a role for AI within a system of educational activity

Figure 1 also indicates the potential for AI (the robot icon) to contribute to the development of the underlying educational goals (SEL development in this example), as well as assisting in mediating both the balancing and reinforcing feedback loops (B1 and R2) associated with emotions. Some of

these envisaged points for interaction are autonomous, where the robot icon appears alone, and some are supervised, where the robot and mortarboard coexist. It is important to note that these potential points of AI support are entirely indicative and the examples that are presented here are general suggestions.

Before exploring Fig. 1 in detail, it is important that we emphasise the cyclical nature of this model. Learning does not happen as a one-off event. Rather the objects of education (SEL development in this example) result in a series of changes in other quantities that are then available for use in future cycles. It is also essential to recognise that the system presented in Fig. 1 is incomplete and forms just one sub-system in a much more complex process. That is, there will be other factors in the larger system connected to the nodes of our model that are not represented here (e.g., resilience). For this reason, it is important that students experience both successes in learning and difficulties. Each will cause different emotional responses, and the larger system will respond in different ways potentially developing attributes like perseverance that are not represented here. Any AI implementations that become incorporated into this system need to ensure that they are designed to respond appropriately to both success and difficulty in ways that enhance the underlying educational objectives without disempowering students or their teachers or shortcutting the learning processes.

Working from our conceptual model (Fig. 1), we propose six general areas where AI may be able to provide mechanisms or approaches that support the learning process. From these we have identified specific elements of learning design that may be targeted for research, improvement, or modification. These objects of transformation and their associated design goals are presented in Table 1 along with possible AI application strategies and examples of implementation.

Firstly, supporting teachers to provide mathematical learning activities that are personalised at an appropriate level of complexity to match the cognitive abilities of individual students is essential. The strengths of current approaches to AI lie in their ability to mimic human processes, using vastly larger quantities of data, and with far greater speed than humans can achieve. When an AI is presented with a problem that is similar to ones it has 'seen' before, then it is reasonable to expect the algorithm to follow a similar process in generating output. Therefore, the implementation of some form of semi-supervised, or even unsupervised, algorithm to analyse each student's past and current learning performance and/or mastery data and to suggest learning pathways for them to follow or to dynamically adjust the task demands to an appropriate level would be a potentially effective use for an AI learning support. Such an implementation would appear at ① in Fig. 1 and provide personalised challenges that maintain an optimal balance between task demand and cognitive quality of instruction. These individualised learning experiences will align with each student's proficiency level, minimising their frustration and enhancing the likelihood of successful learning outcomes. However, personalisation should not be limited to task difficulty alone. AI can help pinpoint specific moments where students struggle, providing feedback that is not only task-focused but also supports positive appraisals of their efforts. For example, AI-driven systems can identify when a student shows signs of frustration or disengagement and offer supportive feedback that highlights their progress and effort rather than solely focusing on task completion. This can help students reinterpret their experiences as opportunities for learning, thereby fostering a more positive self-concept and increasing their motivation. An algorithm such as this would be best suited for general implementation by resource producers, as they would have ready access to the large amounts of data needed to

establish the parameters of the algorithm. However, in a semi-supervised arrangement, some system or process would need to be developed to allow the classroom teacher to provide input and fine tune the algorithm in a straightforward and intuitive way.

Extending the idea of performance monitoring to student self-monitoring, AI algorithms can be used to enhance learners' perceptions of agency and control and might be utilised at ② in Fig. 1. Using a large set of learning performance data a resource producer could develop a predictive model that gives students a selection of recommended next steps for their own personalised learning yet remains within the same area of knowledge that the teacher has assigned. In this conception, the AI algorithm essentially creates a decision tree for building learning pathways but leaves the final step of the process, the decision itself, up to the student. Built into such a predictive system would be the opportunity for learning analytics that could build an understanding of each student's cognitive strengths and weaknesses and provide nudges to assist the student in achieving their own stated goals. AI-enabled tools might also be used in creative learning environments encourage cooperation and thus cultivating positive social interactions. These tools might include interactive and collaborative platforms where students can explore mathematical concepts independently and engage in cooperative problem-solving activities. AI can also contribute to the development of enhanced feelings of control and growth through individualised achievement goal structures and expectations; approaches that are key in reducing maths anxiety.

AI may also assist teachers in enhancing students' value induction ③ which is an important facet of learning success. AI search engines have access to an almost endless volume of information that could be used to select contexts or situations that highlight the real-world applications and uses of mathematical problems in a way that is relevant to individual students. Such an approach can contribute to students' understanding of the intrinsic value of mathematical knowledge¹⁵.

Chatbots based on large language models (LLMs) have become particularly effective in recent years. While chatbots are still far from perfect, the ability to sideload an LLM with an appropriate set of background data files, does offer educators the possibility to use these algorithms in a safe and closed environment while ensuring that the chatbot has access to only appropriate additional information and not the entire unfiltered web. Adopting such an approach has the added advantage that the LLM itself can be smaller allowing it to run on prosumer level local hardware and removing the need to run on massive cloud infrastructure. The use of an AI approach like this to assist students in moderating feedback loops, such as the one at ④, has great potential for research and impact¹⁶. As noted, there is a reinforcing loop between perceptions of control and maths anxiety (R1 in Fig. 1). In a traditional classroom, this feedback loop might be driven by general reflection on the task and its success criteria analysing what the student got wrong and how to fix this. This type of feedback needs to be carefully supervised to ensure that unhelpful self-talk does not dominate the process. An AI chatbot can help to reframe these reflections to consider how an individual has developed in multiple ways while engaging with the learning activities and reduce the dichotomous focus on success vs. failure.

Furthermore, retraining students' notions of failure and success becomes feasible through AI interventions that emphasise the iterative nature of learning and the value of the underlying educational goal. Such AI tools placed at ⑤ could promote the use of personal micro-targets for students and shift the focus of the cognitive process away from the learning activity and onto this deeper learning goal, AI-driven interventions can lead to a shift in student mindset as they learn to view setbacks as opportunities for growth and reduce the anxiety associated with performance.

Table 1 | Mapping the impact of AI implementation in the learning design

Research focus	Ref. (Fig. 1)	Object of transformation	AI implementation	Design goals	Examples
Individualised learning, achievement goals and expectations	①	Task demand and cognitive quality matching	Implement intelligent algorithms to analyse individual student learning patterns and dynamically adjust the task demands and cognitive quality of instruction in real-time.	Tailored learning experiences that align with each student's proficiency level, minimising frustration and enhancing engagement.	+ A student excelling in calculus faces more advanced problems, while another struggling with basic algebra receives simplified tasks. This tailored approach aligns with each student's proficiency level, minimising frustration and enhancing engagement by providing challenges that are appropriately matched to their abilities. – The AI platform struggles to accurately assess individual learning patterns. As a result, a student ready for multiplication is confronted with overly challenging division problems, causing confusion and frustration. Conversely, a student comfortable with multiplication tasks is presented with basic addition, leading to boredom.
	②	Agency and cooperation in learning environments	Incorporate AI-supported adaptive learning platforms that allow students to progress at their own pace, fostering autonomy. Integrate collaborative AI tools to encourage cooperative problem-solving.	Empowered students with a sense of control over their learning journey and enhanced social interactions that positively influence their emotional experiences.	+ In an AI-supported maths platform, a high-performing student working on algebra receives dynamically adjusted tasks. If they excel in solving linear equations, the system challenges them with quadratic equations or introduces more complex variables. – The AI tools create confusion in coordinating efforts among students working on a trigonometry project, leading to unproductive teamwork and hindering a meaningful understanding of the topic. This diminishes the sense of autonomy and positive social interactions among students.
		Individualised achievement goal structures and expectations	Leverage predictive analytics to understand individual student capabilities and set personalised achievement goals. AI-driven recommendation systems can guide students in setting realistic expectations.	Students work towards achievable goals tailored to their abilities, reducing anxiety and fostering a sense of accomplishment.	+ An AI-driven recommendation system suggests realistic targets for a student studying calculus. The student, with guidance, breaks down complex integration problems into manageable steps, achieving goals aligned with their abilities. This approach reduces anxiety, enhances focus, and fosters a sense of accomplishment in mastering challenging mathematical concepts. – A struggling student in algebra receives recommendations for advanced calculus objectives. This mismatch creates undue stress, hindering the learning process and leading to feelings of inadequacy. The lack of accurate goal-setting guidance diminishes the positive impact on student motivation and accomplishment in mathematics.
	③	Improved value induction	Use machine learning algorithms to assess students' preferences and interests, delivering content that resonates with their individual values.	Increased intrinsic motivation as students find personal relevance in mathematical concepts, leading to a positive emotional response.	+ A student interested in architecture explores geometry through designing structures. This personalised approach increases intrinsic motivation, as the student finds direct relevance and personal connection to mathematical concepts, resulting in a positive emotional response and heightened engagement with the subject. – A student passionate about statistics receives content focused on geometry puzzles, creating a disconnect. This mismatch diminishes intrinsic motivation, as students fail to find personal relevance in the assigned tasks, leading to a negative emotional response and reduced engagement with mathematical concepts.
Moderating feedback mechanisms	④	Feedback strategies to preserve sense of control	Implement AI-powered feedback mechanisms that provide constructive guidance (adaptive feedback) without	Constructive feedback that encourages improvement without eroding students' or teachers' sense of control,	+ A student working on a geometry-based task receives feedback from AI that highlights their areas of growth since they last worked on a similar activity 6 months previously. The

Table 1 (continued) | Mapping the impact of AI implementation in the learning design

Research focus	Ref. (Fig. 1)	Object of transformation	AI implementation	Design goals	Examples
			undermining students' confidence.	promoting a positive emotional response to challenges.	ability to frame the feedback within the larger picture of overall growth enhances their sense of achievement and capability and gives them a perception of greater control over future tasks. – A student working on algebraic expressions receives generic feedback that doesn't address specific errors or strengths. The lack of precision in feedback diminishes the sense of control, as students struggle to understand and improve.
Emotion regulation	⑤	Retraining attributions for failure and success	Develop AI-driven interventions that help students reframe perceptions of failure and success through personalised feedback and motivational prompts.	Shift in mindset as students learn to view setbacks as opportunities for learning, reducing anxiety associated with performance.	+ If a student struggles with a challenging statistics problem, the system offers specific guidance on improvement and highlights the effort invested. Motivational prompts encourage viewing setbacks as opportunities for learning. – A student facing challenges in geometry receives generic messages that overlook the deliberate decision by the teacher to allow the student to persevere through difficulties. The lack of understanding and acknowledgement of this intentional teaching strategy hinders the development of skills related to perseverance and independent learning. There is a concern that the reliance on generic feedback may lead students to seek quick fixes and undermine their ability to navigate challenges independently, raising questions about the sophistication of the learning analytics employed.
	⑥	Fostering self-regulation of emotions	Implement emotion-aware AI systems that recognise and respond to students' emotional states. Integrate virtual mentors or chatbots to offer support and strategies for emotional self-regulation.	Enhanced emotional regulation, as students learn to identify and manage their emotions, contributing to a more positive learning experience in mathematics.	+ An emotion-aware AI system in maths recognises when a student feels frustrated while working on a challenging algebra problem. A virtual mentor engages the student, providing supportive feedback and suggesting effective strategies for emotional self-regulation, such as taking short breaks or breaking down the problem into smaller parts. – Despite the implementation of emotion-aware AI systems, the recognition of students' emotional states in maths proves inconsistent. For example, a student struggling with fractions receives no targeted emotional support, as the system fails to detect signs of frustration. The absence of timely interventions hampers emotional self-regulation, leaving the student feeling overwhelmed and negatively impacting their learning experience in mathematics. The limited effectiveness raises concerns about the overall support provided by virtual mentors or chatbots.

However, while current AI tools are capable of 'decision making' using large amounts of mostly structured data, they lack the capability to genuinely understand and adapt to the emotional and cognitive needs of students. The AI models tend to focus more on the mechanics of teaching rather than the emotional well-being of the learner. That is, currently available AI tools are more focussed on the products of learning than on the human process of learning. To truly harness the potential of AI in transforming mathematics education, we need to prioritise different research goals. Researchers should therefore aim to develop new systems and approaches that foster a deeper, more intuitive understanding of

mathematical concepts, rather than just improving the efficiency of content delivery.

For example, we know that self-regulation of emotions is essential in order to manage adverse situations such as maths anxiety. Natural language processing algorithms might be developed to identify the fingerprints of both positive and negative emotional meaning in students' extended textual responses. This might be supplemented with data gathered through multi-modal learning analytics—such as computer vision and audio analysis—to track non-lingual cues such as facial expressions, tonal variation and gestures¹⁷. Together such a dataset might be able to be used to provide

support and strategies, both virtual and real-life, that can assist students in developing their self-regulation and emotional moderation. Such a technology might have a place at ☉ or ☺ in Fig. 1.

An ethical dilemma

With regard to each of the potential applications for AI outlined here and elsewhere their remains an enormous elephant in the room. AI algorithms can only explore patterns in data and provide students and teachers with appropriate feedback if appropriate data is first collected. Thus, it is almost certain that different, or at least modified, didactical tools will need to be developed and used as part of the learning process. Tools already exist that can run on a student's own device to collect digital interaction data and provide individualised feedback when writing. Students may have access to devices to record video and audio to demonstrate their learning processes which can then be uploaded to a learning management system and subsequently analysed in partnership with AI. Training classrooms have been established to capture group interactions using video and audio recognition combined with positional information that can inform educators about the development of group dynamics. However, each of these sources of additional data comes with increased risks regarding data security, increased costs regarding equipment purchase and maintenance, and increasingly complex challenges regarding the ethics of collecting and using the data. Additionally, each source of data will be associated with the need for training and pedagogical changes and will have impacts, both positive and negative, on teacher autonomy, well-being, and flexibility.

In our proposed AI use cases, we need to emphasise the importance of educators and providers using data responsibly and transparently to enhance learning without compromising ethical standards. It is easy to see how any of the approaches suggested here could raise ethical questions around data ownership, privacy, and even a person's right to choose to not engage with a particular tool or technology. However, the details of such discussions would be legion and need to be very specific to the actual technological approach adopted. We will therefore not go further into these points here as much has already been written on the topic of AI ethics^{18,19}. However, we will state definitively that all such concerns *must* be explored in a wide-ranging and good-faith manner *and* emergent issues comprehensively addressed *before* any new technology is implemented. Educational leaders and policy makers must make research-informed decisions rather than relying on intuition or convenience. As historical examples have shown, for example the widespread adoption of LLMs like ChatGPT into every software product under the sun, it is far too easy to put off doing this essential governance until after the horse has bolted, by which point it is too late to consider the consequences and closing the gate is no longer an option.

Agenda for AI implementation research

The integration of AI into mathematics education has the potential to revolutionise the field. It can transform the teacher-student dynamic and holds immense potential for enhancing both academic achievement and emotional responses among students. Addressing issues such as maths anxiety requires a positive impact on students' emotions, particularly in fostering perceptions of competence and control over academic activities. In exploring AI-supported SEL in mathematics education, we propose an agenda that investigates how human-computer interactions go beyond enhancing to actually transform teaching practice²⁰. Our research agenda, centred around three main points, systematically addresses key aspects contributing to SEL and aims to alleviate students' maths anxiety.

(1) Individualised learning, achievement goals and expectations: an interesting avenue of investigation lies in leveraging AI to tailor individual achievement goals and expectations for students. By setting achievable and

realistic goals based on each student's unique abilities, AI can enhance motivation and self-efficacy. This individualisation not only helps in addressing maths anxiety but also fosters a sense of accomplishment as students witness their progress aligned with personalised benchmarks.

(2) Moderating feedback mechanisms: researchers could also explore the integration of AI systems that provide real-time emotional feedback during classroom activities. For example, sentiment analysis algorithms could gauge students' emotional responses to mathematical challenges. Teachers, armed with this data, can adjust their teaching approaches on the fly, offering additional support or introducing activities to alleviate anxiety. Another interesting avenue for research could focus on the development and implementation of AI-driven virtual teaching assistants explicitly designed to provide emotional support. These assistants could engage in natural language conversations with students, offering encouragement, motivation, and strategies to manage maths anxiety.

(3) Emotion regulation: future research could focus on developing and investigating the impact of comprehensive AI-driven student dashboards that offer insights into a student's socio-emotional development and academic progress. These dashboards could generate personalised progress reports that not only highlight academic achievement, but also provide insights into students' emotional responses during maths activities, their collaboration skills, and overall engagement. By making these dashboards accessible to students, AI serves as a bridge, facilitating transparent communication and metacognitive discussions, as well as supporting emotion regulation. These elements are all essential in both preventing and addressing the symptoms of maths anxiety^{21,22}.

We propose a multi-method approach to investigate the effectiveness of AI implementations in addressing SEL and maths anxiety. The methodology we suggest includes a combination of qualitative (e.g., interviews and focus groups with educators and students, case studies) and quantitative methods (e.g., surveys, psychometric assessments) to capture a comprehensive view of the impact of AI-driven interventions. Additionally, experimental studies can be designed to test the effectiveness of specific AI interventions, comparing traditional teaching approaches with AI-enhanced learning environments.

To address the complexities of human-computer interactions, we advocate for a structured research approach incorporating both detailed case studies and longitudinal studies. Specifically, we propose conducting case studies in diverse educational settings that observe how students and teachers interact with AI tools across varying socio-economic and cultural contexts. These case studies would include the use of video recordings of classroom interactions, detailed logs of AI feedback loops, and interviews with teachers to identify specific instructional adjustments made in response to AI insights. Additionally, longitudinal studies should follow cohorts of students over the course of an academic year, tracking their progress through regular psychometric assessments, classroom observations, and emotional feedback reports. By triangulating data from these methods, researchers can capture the nuanced shifts in students' perceptions of competence, control, and anxiety. Such an approach would also allow for the identification of key factors that enhance or hinder the long-term effectiveness of AI interventions in transforming teaching practices and emotional responses to mathematics learning.

In essence, the proposed research agenda envisions AI not merely as a tool for product-oriented tasks but as a transformative force, where human-computer interactions lead to an expansion of practice. Through this framework, we seek to go beyond the conventional understanding of AI in education and explore its potential to reshape teaching practices fundamentally. By delving into the nuanced ways in which AI can enhance emotional responses, foster perceptions of competence, and provide

support mechanisms for students experiencing maths anxiety, this research agenda aspires to offer practical solutions that transform the educational landscape. Ultimately, this endeavour envisions AI not only as a facilitator of academic achievement but as a catalyst for a profound shift in the dynamics of mathematics education, emphasising personalised and emotionally supportive approaches.

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Author contributions

F.G. was responsible for the conception of the manuscript. F.G., J.K., R.M., and S.L. contributed to the writing and editing of the manuscript. All authors have read and approved the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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