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Collaboration, Creativity and Compassion in a Digital Society

Can GenAI numeracy tutors support self-regulated learning?

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Generative artificial intelligence (GenAI) has been the focus of much attention in the higher education sector, both for its potential to support personalised and adaptive learning, but also due to the risk that students may outsource learning to it, leading to gaps in their professional or discipline competencies. This risk of cognitive offloading applies equally to learning how to learn, a skill set explored through studies of self-regulated learning (SRL). Two GenAI numeracy tutors were piloted at a regional Australian university as one component of a newly launched mathematics and statistics support centre, one focusing on medication calculations for Nursing students (NiNA), and the other on threshold numeracy skills for Education students (EdNA). Detailed analysis of students' conversations with these agents using Zimmerman and Moylan's 2009 SRL framework revealed extensive evidence of some elements of SRL such as strategic planning, task-specific strategies, and adaptive competence; trace evidence of other elements including self-efficacy and self-evaluation; and no evidence of the remaining elements. This study contributes an underrepresented qualitative perspective to the body of research into the crossover of GenAI and SRL and foreshadows avenues for further research and refinements in the design of GenAI numeracy tutors.

Keywords: self-regulated learning, generative artificial intelligence, adaptive learning, help-seeking, directed content analysis

Introduction

Supporting students who do not meet the explicit or implicit numeracy expectations of their higher education studies has been an objective of university mathematics and statistics support centres in Australia and internationally for many decades. The progressive relaxation of mathematics pre-requisites for Australian degrees (Finkel et al., 2020; Tsui & Khan, 2023), coupled with an increasingly diverse, off-campus, and part-time student cohort, has made upscaling and increased flexibility of support ever more pressing. Generative artificial intelligence (GenAI) tutors offer a promising additional strand of support, owing to their scalability, 24/7 availability, online access, and ability to tailor instruction dynamically as they interact with students. Caution is nevertheless called for, as this same technology can be used for cognitive offloading such as completing assignment questions, and over-reliance on adaptive learning tools may detract from students' ability to learn to make their own decisions about how they learn, the essence of self-regulated learning (SRL).

At a regional Australian university, we trialled two GenAI numeracy tutors as part of a newly launched mathematics and statistics support centre. The tutors were designed to support our two largest cohorts needing numeracy support: Nursing students for medication calculations, and Education students who in Australia must pass a numeracy threshold test for teacher registration. The tutors were built with Cogniti, a generative AI platform developed by educators at the University of Sydney and purpose-designed to support the creation of AI-driven learning agents within higher education contexts. The architecture of Cogniti allowed the agents to be embedded directly within the unit-level LMS, enabling contextually situated access for students instead of requiring engagement with an external tool. The agents were named NiNA (Numeracy in Nursing Agent) and EdNA (Education Numeracy Agent); which were focused on working through practice questions with the student. The design of both agents was developed collaboratively with the teaching academics responsible for the supported units, ensuring disciplinary accuracy and contextual appropriateness. Drawing on Socratic tutoring principles (Collins et al., 1989), the agents were iteratively prompt engineered to guide students toward correct answers through questioning and scaffolded reasoning, rather than providing direct solutions, a deliberate design decision intended to engage active knowledge construction rather than passive answer retrieval. Consistent with Zimmerman's (2000) self-regulated learning framework, the agents were also prompted to offer reflective feedback at set intervals throughout each interaction, inviting students to evaluate their own understanding and consolidate learning before progressing.

We have reported elsewhere on the effectiveness of NiNA and EdNA as numeracy tutors, notably on the high proportion of cases in which the tutor successfully guided students to the correct answer (Camacho et al., 2026). With this study we wanted to investigate the extent to which student interactions with GenAI numeracy tutors supported or hindered the development of self-regulated learning skills. This was of particular interest given our cohort: students from diverse backgrounds who may not have well-developed SRL abilities. We made use of the SRL framework of Zimmerman and Moylan (2009), which constructs SRL as a cycle of three phases encompassing 20 elements (Figure 1), and carried out directed content analysis (Hsieh & Shannon, 2005) of the transcripts of student-agent conversations, with the aim of identifying instantiations of these 20 elements in student-tutor interactions. We used this analysis to make inferences about the extent to which SRL processes were apparent in students' interactions with these tutors.

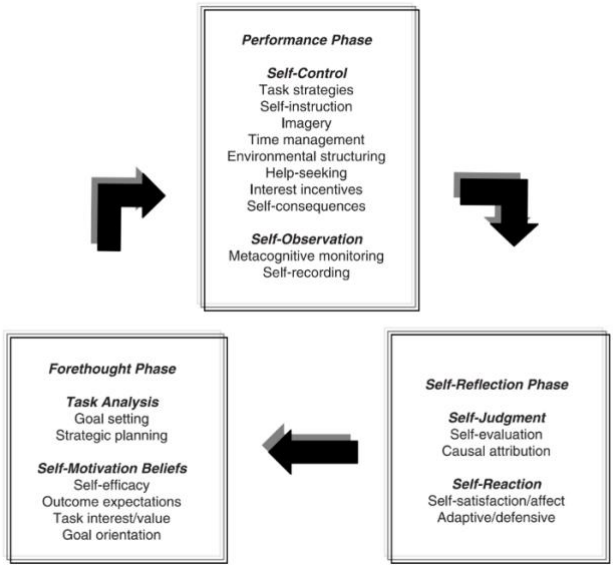


Figure 1. A cyclical phase model of self-regulation that integrates metacognitive processes and key measures of motivation (Zimmerman & Moylan, 2009). Copyright 2009 by Imprint. Reproduced by permission of Taylor & Francis Group.

Literature

Self-regulated learning (SRL) emerged as a theoretical construct which was grounded in Bandura's (1986) social cognitive theory and formalised by Zimmerman (1989, 2000) as a goal-directed process through which learners cyclically monitor, evaluate and adapt their learning behaviours. Alongside Flavell's (1979) earlier work on metacognition, SRL frameworks position learners as active agents who are capable of directing their cognitive and motivational resources. This conceptualization created a shift in educational research from what instructors do to how learners actively manage their own learning processes.

Research has shown that students' self-regulatory capabilities can significantly influence how effectively they engage with online learning environments (Lin, 2022) and how they find their way in learner-directed pathways which require increased autonomy and personal responsibility (Crosslin, 2018), highlighting that educational technologies do not inherently promote learning but instead are effective by the extent to which they support self-regulatory processes. Recent advances in GenAI have garnered rapid traction in higher education due to its capacity to provide immediate explanations, feedback and personalised support (Thompson et al., 2023). Critics argue that GenAI risks undermining SRL by enabling cognitive offloading, reducing metacognitive effort, and fostering passive help-seeking behaviours in which students receive answers rather than constructing understanding (Darvishi et al., 2024; Kasneci et al., 2023). However, proponents of GenAI suggest that genuine opportunities to scaffold and extend SRL are possible. When designed with pedagogical intent, through means such as Socratic prompting and adaptive feedback, AI tutoring systems can induce learners to monitor their own understanding, set goals and reflect on

performance that is conducive to the self-reflection phase of Zimmerman's (2000) cyclical model (Molenaar, 2022).

A number of models of SRL have been developed to aid inquiry (Panadero, 2017). The Zimmerman and Moylan SRL framework (2009), adapted from a model originally developed by Zimmerman (1989; 2000), conceives of self-regulated learning as a cycle of three phases: a forethought phase consisting of task analysis and self-motivation beliefs; a performance phase comprising self-control and self-observation; and a self-reflection phase encompassing self-judgement and self-reaction (Zimmerman & Moylan, 2009). A more detailed description of this SRL model will be provided alongside an account of our coding conventions and the provision of results in the results section, below. While a range of similar models exist, the Zimmerman and Moylan framework was selected for our analysis owing both to its widespread use in scholarship (Banihashem et al., 2025; Panadero, 2017), and the compatibility of its categories with our data.

While research into AI-supported SRL development has grown in recent years, comparatively little has been qualitative, and only a minority of studies represent health and education disciplines (Banihashem et al., 2025). A recent qualitative systematic review in the higher education context has noted the "paucity of research specifically exploring AI's role in SRL" (Lan & Zhou, 2025, p. 1). Support operationalization frequently relies on parallel information provision, typically via a dashboard which students are expected to monitor, or through predictive profiling (Banihashem et al., 2025). Given the use of a GenAI tutor already represents help-seeking, a key SRL behaviour (Broadbent & Lodge, 2021; Zimmerman & Schunk, 2012), and given the absence of social barriers to help-seeking and self-direction of learning, which may influence interactions with human tutors, we wanted to investigate the extent to which SRL skills were supported through the learning activity itself, as well as to gain information about how the tutors' prompts could be improved to better support SRL.

Method

We carried out detailed content analysis of the transcripts of students' conversations with the two agents in the second half of 2025. After opt-outs were removed, in accordance with our ethics approval, there were a total of 134 conversations involving 77 unique students. We applied the directed content analysis methodology of Hsieh and Shannon (2005), whereby coding categories were taken directly from our selected theory of self-regulated learning (Zimmerman & Moylan, 2009). In line with our methodology, which can be used to extend a theory, we added two further categories to this SRL framework, drawing from related work by Zimmerman collaborator Schunk (1998).

Two of the authors (CB and LC) iteratively refined the coding criteria for each category, by applying them to small samples of data. Complete coding was then carried out by one author (CB). The other coding author (LC) then blind-coded a sample (approx. one third), and the coding of the sample by the two authors compared. As will be discussed in the results section, some codes were represented strongly in our data, while others only applied to a very small number of comments (and some were not present at all). Cohen's Kappa (Cohen, 1960), measuring inter-rater reliability, ranged from 0.60 to 0.88 across the codes that were represented extensively. Cohen's Kappa in the range 0.41-0.60 is considered moderate agreement, in the range 0.61-0.80 substantial agreement, and in the range 0.81-1.00 almost perfect agreement (Landis & Koch, 1977). We considered these inter-rater reliability measures to be acceptable, given our results were intended to be indicative only, and were not used for any further quantitative analysis, in line with our directed content analysis methodology (Hsieh & Shannon, 2005). For the codes with only a small number of counts (25 or fewer across the full data set), the two coding authors met to discuss each case, ensuring agreement. Additionally, we made use of the time-stamps in the Cogniti records to aggregate the times of day when students were accessing the agents. Student quotations are referred to via the pseudonyms NiNA Student 1-50 and EdNA Student 1-27. There was no overlap between the two cohorts. This research was approved by the Human Research Ethics Committee of Federation University Australia (approval number 2025/120).

Results

We analysed the transcripts of students' interactions with NiNA and EdNA for evidence of the features of the three phases of the Zimmerman and Moylan social cognitive model of self-regulation (2009). Conversations

consisted overwhelmingly of clearly identifiable cycles, typically starting either with a request for practice questions, or for a topic explanation leading into a practice question, followed by discussion focused on supporting the student to solve the problem; a confirmation of the solution, which often involved a restatement of the working; before finally returning to the start of the cycle, either with further practice on a similar question, or taking up a new topic. At the end of every three or four such cycles, the agent was prompted to elicit the student's reflection on progress, which proved a rich source of data. These cycles could be aligned without difficulty with the three-phase cycle described in the Zimmerman and Moylan model of SRL (2009).

Forethought phase

In the Zimmerman and Moylan SRL model (2009), the forethought phase consists of *task analysis* and *self-motivation beliefs*. Task analysis itself has two components. *Goal setting* refers to a concrete, time-specific aim, such as completing a question sheet in an hour. In our data goal setting was mainly exemplified by the intention to work through an unspecified number of practice questions. Other forms of goal setting were more qualitative, such as "Help me understand unit conversion" (NiNA Student 4). *Strategic planning* refers to selecting learning methods. Here there were three main approaches: asking the agent for practice questions related to the strategic goal, entering a practice question from elsewhere which the student wanted to work through, and asking for a topic explanation, which then normally led to the agent (or in a few cases the student) providing a practice question to check understanding. Our data contained many examples in both task analysis sub-categories.

Concerning self-motivation beliefs, Zimmerman and Schunk have observed that "SRL skills don't work without motivation" (2012, p. 3). The Zimmerman and Moylan SRL model identifies six key sources of motivation. The first, *self-efficacy*, arising from the work of Bandura (1977; 1997), is a widely used concept in educational research. In the context of the SRL framework, Zimmerman and Schunk (2012) have stressed that self-efficacy refers to confidence in the specific learning context, not general self-confidence in one's ability to learn. Students only occasionally provided information about their current level of self-efficacy, and this was usually as a result of prompting by the agent, at the end of a problem-solving cycle. Even then, actual expressions of confidence (e.g., "They're [the practice questions] very useful! I'm more confident," NiNA Student 47) were rare, and confidence was usually implied through requesting more challenging questions. Because of the cyclic nature of Zimmerman and Moylan's SRL model, we interpret these expressions of self-efficacy as representative of self-motivation in the forethought phase of the following cycle. *Outcome expectations* refer to social status improvement or occupational goals (Zimmerman & Moylan, 2009). There were no comments encapsulating such outcome expectations; however, as both agents were designed to prepare students for professional registration testing requirements, the outcome expectations of becoming a nurse or a teacher are implicit. *Task interest/value* refers to a quality described by Self-Determination Theory as intrinsic motivation (Deci & Ryan, 1985; Ryan & Deci, 2000). While it is unlikely our target cohorts (i.e. students in need of supplementary numeracy support) would experience much intrinsic motivation when it came to preparing for compulsory mathematics tests, there were isolated examples of students asking more exploratory, conceptual questions, for example, "why do numbers to the power of zero equal 1?" (EdNA Student 20), which could be interpreted as demonstrating intrinsic motivation. Such examples were rare, however. *Goal orientation* refers to the differentiation between a learning goal orientation, reflecting an inherent desire to improve one's skills, versus a performance goal orientation, which prioritizes favourable comparison with one's peers (Zimmerman & Moylan, 2009). Our data provided no information on goal orientation.

Performance phase

The performance phase consists of *self-control* and *self-observation*. The first component of self-control is developing *task-specific strategies*, such as deciding on the steps to take in solving a mathematics problem (Zimmerman & Moylan, 2009). While our data do not contain explicit statements of strategies, occasionally students would ask for the relevant formula ("I FORGOT, CAN YOU GIVE ME THE FORMULA," NiNA Student 27), indicating a plan to proceed by applying it. More frequently students would show their steps while working through a problem, giving an indication of their task-specific strategy ("140 - 84 = 56 so ratio of pet-owning to non-pet owning is 84:56 divide by 4 21:14 divide by 7 = 3:2," EdNA Student 10).

The next five elements of the Zimmerman and Moylan model refer to general, rather than task-specific learning strategies. *Self-instruction* refers to "overt or covert descriptions of how to proceed as one executes a task" (Zimmerman & Moylan, 2009, p. 302). In the case of children learning mathematics, this includes train-of-though verbalization (Schunk, 1982). There were occasional examples of this happening in our data (though obviously typed and not actually verbal), typically prompted by a "how" question from the agent, for example:

> EdNA: What steps would you take to simplify this fraction?
> Student 2: Find a number that divides both the top and bottom of the fraction.

As noted above, some students also chose to give a running explanation of how they arrived at a particular answer. We coded this behaviour as both indicative of a task-specific strategy and a demonstration of self-instruction. There was only one use of *imagery* in our data, and that was prompted by the agent. In response to the student requesting a different approach to the one being pursued, NiNA suggested:

> Let's try a different approach by using visuals or real-world examples to explain dosage calculations. Imagine you are preparing a medication for a patient who needs 500 mg of a drug, and you have a bottle labelled 100 mg/mL. Think of the bottle as a container holding small 100 mg portions of the medication in each mL. To give the required 500 mg, how many of these 100 mg portions do you need to use? Each portion is 1 mL, so how many mLs would you administer? Would visualizing it this way help? What do you think? (NiNA, in response to Student 31)

The student later indicated that this use of imagery was useful. This was an isolated case, however. There was also only a single case of *time management* being discussed, this time emanating from the student, who requested a study plan to cover the main numeracy topics in the LANTITE test within a two-day preparation period (EdNA Student 24). *Environmental structuring*, meaning deliberate choice of tools to improve performance or of surroundings to increase concentration (Zimmerman & Moylan, 2009; Zimmerman & Schunk, 2012), did not emerge explicitly from the data, however there are strong indicators that students found engaging with the agents at a time and place of their choosing beneficial: 59% of NiNA conversations were commenced outside of office hours, as were 50% of EdNA conversations. The next factor pertaining to self-control in the performance phase of the Zimmerman and Moylan SRL model (2009) is *help-seeking*. This is represented most strongly in our data, as all conversations with agents were examples of students engaging in help-seeking behaviour. We return to this point in the discussion section.

The final two elements of self-control refer to motivation rather than metacognitive strategies (Zimmerman & Moylan, 2009). *Interest incentives* are provided by superstructures such as gamification or peer competition. While there is little direct evidence of interest incentives in our data, it is possible that students found the positive, chatty nature of interaction with the agent a feature that increased their interest. The following is a possible example of this:

> NiNA: Would you like to continue with more mixed questions, or is there another aspect of dosage calculations you'd like to explore or feel you need to practice more?
> Student 6: Just random I think I'm pretty good but I'm having fun.

Finally *self-consequences* are self-imposed disciplinary regimes, such as deciding to complete a certain number of questions before taking a break. There were no examples of this category in our data.

The self-observation component of the performance phase refers to tracking of performance, which can be done either mentally and informally, referred to by the model as *metacognitive monitoring*, or through *self-recording*, "creating formal records of learning processes or outcomes" (Zimmerman & Moylan, 2009, p. 303). Though instigated by the agent, rather than the student, there were occasional examples in our data of recording, such as when NiNA stated, "You've now answered four questions successfully!" (to Student 47). Schunk has observed that for children, external monitoring (progress recorded by the teacher) was just as effective as self-monitoring in maths lessons (1998). Furthermore, it is likely that students maintained a general awareness of their success rate with practice questions as a form of metacognitive monitoring, although there is no direct evidence of this occurring. In the Cogniti platform it is also possible for the student

to review past conversations, as a record of learning processes or outcomes. While we do not have any information on whether students actually made use of this provision, it is quite possible that students scrolled up to see how a similar problem was solved last time. In future this could be interrogated through additional research instruments such as a post survey, focus groups, or interviews.

Self-reflection phase

The self-reflection phase consists of *self-judgement* and *self-reaction*. The first element of self-judgement is *self-evaluation*, which refers to evaluation of performance compared with a standard (Zimmerman & Moylan, 2009). There were only occasional examples of this in our data, and these were usually prompted by a reflection question coming from the agent, as the following example demonstrates:

> NiNA: You've answered several questions correctly now! How are you feeling about these calculations? Are you finding them easier to work through?
> Student 22: I am still learning however am feeling ok with it.

In this and other cases the act of self-evaluation ("I am still learning") was coupled with an element of self-reaction ("feeling ok with it"), addressed below. We included expressions of confidence both in this self-evaluation category, and in the self-efficacy category of the forethought phase of the subsequent cycle. *Causal attribution* is recognised by SRL scholars as highly significant, because blaming poor performance on an immutable property, such as not being smart enough, is detrimental to SRL, whereas attributing failure to something over which the student has control, such as a poor choice of strategy or insufficient effort, opens up the possibility for adaptation and subsequent improved performance (Zimmerman & Moylan, 2009). There were only isolated examples of causal attribution, such as the following comment ("I'm horrible at maths"), already referred to above under time management. Its context, however, would appear to indicate that the student felt they were talking about a controllable factor:

> EdNA Student 24: Okay I want to learn and focus more on the maths that is on the lantite test! Please come up with a plan for me to learn/study it all the in the next two days keeping in mind I'm horrible at maths.

Self-reaction is described as "cognitive, affective, and behavioural responses to self-judgments of one's progress in achieving a goal" (Zimmerman & Schunk, 2012, p. 19). *Self-satisfaction/affect* refers to cognitive and affective reactions, and though only appearing occasionally in our data, tended to be linked to self-evaluations, as exemplified by the extract "however am feeling ok with it" (Student 22) also cited above. Again, these were typically prompted by a programmed reflective question from the agent. Finally, the *adaptive/defensive* category covers the behavioural response to self-judgements. Adaptive behaviour refers to decisions either to continue with the same approach to learning if it is working, or to adapt the strategy if it is not. Defensive behaviour is a negative reaction to self-judgement, corresponding to loss of interest in further learning, as a defence against failure (Zimmerman & Moylan, 2009). There were many examples of adaptive behaviour in our data, including continuing with the current strategy: "Can I have another practice question on number?" (EdNA Student 22), requesting the removal of scaffolding and increasing the difficulty of the practice questions: "I'm about 60 percent confident can you give me some harder questions and put in real life lantite style" (EdNA Student 24), moving to a new topic after gaining confidence in the current one: "more questions new topic" (NiNA Student 26), and lowering the level of practice questions to align better with the student's perceived ability:

> NiNA Student 5: We have[n't] learnt that yet but I will give it a go
> [Student unsuccessfully attempts an intravenous infusion rate question]
> NiNA Student 5: Can you not include these sort of questions.

In the majority of cases, adaptive decision making was the student's initiative (203 cases out of 326), however there were also cases of students reacting to an agent's suggestion, such as the following:

> NiNA: That's correct, you would administer four capsules. Would you like to try another question, perhaps with a different form of medication or a different calculation challenge?
> Student 30: Yes different form.

Defensive behaviour would most likely have been exhibited by a decision to discontinue the discussion, though that of course would not be the only reason for a discussion ending. An argument could be made that breaking off a conversation after failure to answer a question might represent defensive behaviour. However, in our data there were only two cases (EdNA Students 1 and 9) of the student giving up on an attempted question, leaving the conversation, and never returning to the agent.

Modelling and positive feedback

Parallel to the Zimmerman and Moylan (2009) SRL model, we also considered two further categories that have been highlighted by scholars, including Schunk, one of the founders of SRL theory, as salient to the social-cognitive model of self-regulation. These are modelling and feedback. Schunk has argued that *modelling* positive behaviour (e.g., a teacher demonstrating an approach to solving a problem) is a key avenue for nurturing the development of self-regulated learning skills (Schunk, 1998). More recently Russell et al. (2022) found support for the significance of modelling in teaching self-regulated learning in the higher education context. There were many examples of modelling of problem-solving steps by the agents in our data, illustrated by the following extract:

> Student 35: Can you explain the steps in detail?
> NiNA: Certainly! Let's go through each question step by step.
> Question 1: Injection Calculation
> To find out how many mL of medication you should administer, you can use the formula:
>
> $$Volume\ to\ give\ = \frac{Dose\ Ordered}{Stock\ Strength} \times \frac{Volume\ of\ Stock\ Solution}{1}$$
>
> Can you try applying this formula to the first question? What do you get for the Dose Ordered and the Stock Strength?

The agents also very frequently reiterated worked solutions at the end of a problem-solving cycle, once the correct answer had been arrived at. This was the result of explicit instructions in their prompts.

Finally, Schunk has also argued for the value of *positive feedback* from the teacher in building self-efficacy (1998). While we have noted the rarity of direct references to self-efficacy in our data, there were many examples of the agent providing positive feedback on the student's progress, such as "Excellent work! Would you like another question?" (EdNA to Student 21). It should be noted that Schunk's observations on the effect of positive verbal feedback on self-efficacy were in the context of primary mathematics education; furthermore, it is not known whether AI models, renowned for their sycophantic behaviour, could bring about the same results with their feedback. Nonetheless, more recently Bellhäuser et al. (2025) have also established the value of general, confirmative feedback on university students' SRL. Our results are summarized in Table 1 and categorized according to prevalence in our data. Because we are only interested in indicative frequencies of codes, for the purposes of broad comparison counts for individual codes have been omitted.

Table 1.
Summary of evidence of the elements of the three phases of SRL in our data

Phase	Extensive evidence (137-892 counts)	Trace evidence (1-25 counts)	Implicit only	No evidence
Forethought	Goal setting Strategic planning	Self-efficacy Task interest/value	Outcome expectations	Goal orientation
Performance	Task-specific strategies Self-instruction Help-seeking	Imagery Time management Interest incentives Self-recording	Environmental structuring Metacognitive monitoring	Self-consequence
Self-reflection	Adaptive/defensive	Self-evaluation Causal attribution Self-satisfaction/affect		
External elements	Modelling Positive feedback			

Based on Zimmerman & Moylan (2009).

Discussion

Adaptive learning tutors have been criticized for expropriating from students' crucial decision-making over learning strategy effectiveness, thus stunting the development of self-regulated learning skills (Darvishi et al., 2024; Harati et al., 2021; Molenaar, 2022). However, our analysis of conversations between students and AI tutors revealed a high degree of student agency in directing cyclical learning processes, supporting the findings of other studies showing that adaptive learning platforms can be designed in such a way as to enable student agency and support for SRL development (e.g., Alrawashdeh & Castillo, 2025; Lin et al., 2026). Students typically commenced a session with the evident goal of improving their understanding of a topic and/or working through practice questions. They also frequently exhibited indications of possessing strategies on how to proceed on a given problem and were able to change the direction or focus of the session according to perceived success or difficulty. The AI tutors exhibited extensive modelling and positive feedback, which have also been linked to the development of self-efficacy and self-regulated learning skills (Russell et al., 2022; Schunk, 1998). Significantly, all interactions with the two AI maths tutors were examples of help-seeking behaviour, identified as a key component of self-regulated learning (Broadbent & Lodge, 2021; Zimmerman & Schunk, 2012). While it seems likely that the 24/7 availability of our AI tutors and the absence of social barriers to accessing assistance did increase help-seeking behaviour, further research is needed to confirm this hypothesis.

Trace evidence of further components of SRL indicates that interactions with AI tutors were capable of surfacing these elements, suggesting that through refinement of system prompts it may be possible to elicit these indicators more consistently. Making gauges of key elements of self-regulated learning explicit, such as self-efficacy, self-evaluation, interest incentives, causal attribution, and self-satisfaction, may allow the AI tutor to tailor interactions more effectively to individual students' SRL needs, and raise students' meta-awareness of enabling and inhibiting factors. As noted above, many AI interventions seek to develop SRL skills explicitly, distinct from learning activities, for example through the provision of a dashboard (Banihashem et al., 2025), whereas our focus here was on whether SRL skills could be developed through learning activities themselves. Maintaining a record of a student's progress through the practice questions may also support better adaptive decision making by the student. The use of imagery and time management advice could also be offered explicitly, where appropriate, through additional instructions in the system prompt.

There are also elements of the SRL framework that we would not expect to appear explicitly in the conversation transcripts. There is good reason to believe that outcome expectations are strongly implicit: students interact with the tutors because of the requirement to pass numeracy tests for professional registration as nurses or teachers, corresponding to occupational aims. We also interpret the ease of online access and the majority out-of-hours usage of the tutors as indicative of environmental structuring. Finally, while metacognitive monitoring is by definition not recorded, it is not unreasonable to assume that most

students would maintain a mental impression of their progress through successive practice questions. These assumptions could be confirmed in future research via surveys, focus groups, or interviews with students.

Finally, our data contained no evidence, explicit or implicit, of the remaining two SRL categories, goal orientation and self-consequence. Students may well compare results on numeracy tests with their peers, in which case performance goal orientation may be a factor; on the other hand, it appears unlikely that students interacting with supplemental numeracy support agents would be doing so out of learning goal motivation (an inherent desire to learn). We would also not expect to find evidence of self-consequence in our data, though it

is always possible that students set themselves a reward for completing a set quantity of work. These final two SRL indicators could also be investigated in future research through surveys, focus groups, or interviews.

Limitations

We acknowledge that this study represents early research on one specific type of AI tutor. Furthermore, the context is limited to a single institution, albeit across two distinct disciplines. However, we present these outcomes as part of an ongoing research project, with the intention of reaching more robust and generalizable conclusions in the future. Specific areas for further research have been identified throughout the article.

Conclusion

Our analysis of students' conversations with GenAI tutors found many examples of students demonstrating key SRL skills. Once help-seeking is actuated, a behaviour we hope is made more likely by 24/7 availability and the absence of social barriers, students show significant agency in directing their interactions with the tutors, in particular through goal-setting, trialling and refining problem-solving strategies, and conscious adaptation according to their perceptions of success or otherwise. Moreover, self-regulated learning theory expects incremental and repeated experiences of success to increase self-efficacy and motivation (Schunk, 1998; Zimmerman & Schunk, 2012). Self-determination theory also identifies autonomy as a key source of motivation (Ryan & Deci, 2000). At the same time there was little or no evidence of several other elements of SRL in our data: neither do we expect SRL to be developed through one single learning activity.

Our results suggest three areas for further research: firstly, the addition of further qualitative research tools such as surveys, focus groups, or interviews, to map those elements of the SRL model that were unobserved, or assumed to be implicit. Secondly, the development of the tutors' system prompts to better elicit and incorporate indicators of those elements of SRL that were underrepresented in our data (or not present at all), and the evaluation of these enhancements. Thirdly, explicit measures of SRL skills, pre and post tutor use, would provide objective evidence of the extent to which SRL is actually developed in students.

No learning activity exists in isolation. GenAI tutors, should they prove effective, will only ever be part of an ecosystem of learning which includes student-teacher and peer-to-peer interaction, as well as a range of asynchronous activities. Students will also likely only be motivated to use GenAI tutors constructively in the context of an assessment landscape that also requires independent demonstration of skills. A learning tool which is able to develop SRL inherently through unit-specific learning activities, not merely as an add-on would be a valuable addition to this ecosystem.

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