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The role of self-awareness and reflection in academic achievement: A psychological and Bayesian analysis

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ABSTRACT

The ability to properly evaluate one's own academic progress has long been considered a predictor of academic success. However, its distinctive role in the context of computational mathematics remains underexplored. Grounded in social cognitive theory, this study investigates the critical role of self-regulated learning (SRL) strategies in enhancing mathematics learning, particularly in programming-based contexts. Focusing on two components of SRL, self-awareness and reflection, the study provides empirical evidence on the psychological effectiveness of SRL in academic outcomes through the implementation of an e-portfolio-based intervention. Using Bayesian inference, the study models individual learning processes, offering personalized insights for effective educational interventions. The analysis reveals that the use of e-portfolios significantly fosters self-awareness and enhances learning among students. Nevertheless, the study also addresses psychological challenges in programming-based mathematical education, such as complex problem-solving and abstract thinking. The findings highlight the need for interactive, technology-enhanced teaching approaches to keep university-level students engaged and motivated. Key psychological implications are discussed for relevant measures in mathematics education.

Keywords: Bayesian inference, reflection, maximum a posteriori probability, mathematical education

INTRODUCTION

Motivation

With the advancement of technology and smart programming tools, the psychology of learning and teaching must be prioritized. These tools have the potential to elevate student learning to new levels of excellence. However, they can also create significant barriers for students who experience hesitation and fear due to a lack of prior programming knowledge. Overcoming this fear is possible through strategic educational approaches. Teachers can adopt self-regulated learning (SRL) techniques and consider psychological learning aspects to support their students better. This research is devoted to a case study that highlights the importance of effective strategies for improving students' learning skills. It delves into the psychology of learning and teaching, offering useful approaches that can empower students to overcome their fears and enhance their educational experience.

Inspired by recent research, where Nolan et al. (2024) analyzed the importance of centering psychological literacy in undergraduate psychology education internationally, it is evident that the psychology of learning and teaching must be prioritized alongside technological advancements. Hulsbergen et al. (2023) explored the use of online simulations in teaching dialogue skills, demonstrating the potential of smart programming tools to enhance learning. However, these tools can also create barriers for students who fear programming due to a lack of prior knowledge. Gurung et al. (2023) emphasized the role of self-efficacy in coping and learning during the pandemic, highlighting the need for teachers to adopt SRL techniques. By integrating these psychological learning aspects, educators can help students overcome their fears and enhance their educational experiences. This research, devoted to a case study, underscores the importance of effective strategies that improve students' learning skills and psychological resilience in the face of technological challenges.

While the significance of self-awareness in general education has been well noted, its distinctive place in the context of computational mathematics has yet to be fully investigated. The complex nature of programming based subjects (for example computational mathematics, that is dealt with during this research) requires a great deal of abstract and critical thinking, which often presents students with a variety of academic difficulties. Kang et al. (2023), for example, found that students face difficulty with the abstract nature of computational mathematics. They struggle to understand fundamental ideas such as algorithmic thinking and numerical procedures, causing confusion and dis- satisfaction among them. Moreover, Wong (2024) points out that the students with low strong problem-solving abilities find it difficult to apply the knowledge of theory to the practical computational problems, leading to a gap between comprehension and implementation. Besides, Rich et al. (2024) argue that high cognitive workload of computational mathematics can impede students' performance and overall experience in learning as well. Within computational mathematics, where problem-solving confidence, and strategic thinking are critical, self-awareness may significantly affect students' abilities to manage their cognitive load, recognize and debug errors, and solve difficult tasks. Loksa et al. (2016) discussed in detail the effect of explicit guidance for solving programming based exercises. Yet, how self-awareness contributes to performance in computational mathematics, particularly through intervention-based approaches, has generally been under-researched.

Our study thus aims to bridge this gap, describing how improving self-awareness can change the experiences and performance of students in a computational mathematics class- room. This study was also unique in that it employed Bayesian analysis. The conventional education research studies are based on frequentist-based statistics methods which do not allow experience or human knowledge to be considered as prior information and hence sample size is sometimes not sufficient. In contrast, the Bayesian approach offers numerous advantages such as the incorporation of prior information, probability interpretations of findings, and the effective handling of complex models and smaller sample sizes (Howson & Urbach, 2006; Humphreys & Jacobs, 2015). This methodological innovation improves the validity and generalizability of our results, providing us with more fine-grained and empirically sound conclusions about the effects of the interventions. Through the utilization of Bayesian analysis, this research study aims to produce empirical evidence in demonstrating the potential for future advances in methodologies within educational research, ensuring more robust outcomes in the future.

Theoretical Framework

The psychology of learning and teaching involves understanding the mental processes that influence how individuals acquire knowledge and skills. Central to this is the concept of metacognition, which refers to learners' awareness and regulation of their own thinking processes. Additionally, the role of intrinsic motivation, or the internal drive to learn, plays a crucial part in educational outcomes. The use of scaffolding, where instructors provide successive levels of support to facilitate learning, and formative assessment, which involves continuous feedback to guide student improvement, are essential pedagogical strategies.

Social cognitive theory (SCT) has served in the domains of teaching and learning very effectively. In a chapter entitled "Self-efficacy beliefs" in Peterson et al. (2009), SCT is defined in a comprehensive manner as an agentic and empowering psychological perspective in which *"individuals are proactive and self-regulating rather than reactive and controlled either by environmental or biological forces"*.

Inspired from this and other leading research contributions, where the significance of SCT to improve computational mathematics learning (Lent et al., 2018; Mozahem, 2022; Schunk & DiBenedetto, 2020) is reported, during this research, we have used SCT in a novel way, where Bayesian inference is used to track and analyze students' interactions with the programs and algorithms of mathematical computing (as learning materials). The data from e-portfolios was used to develop this inference framework. By analyzing the interactions in this manner, Bayesian inference helped to identify patterns and behaviors that lead to successful learning outcomes and provided personalized feedback to help students become more aware of their learning habits.

The students were allowed to compile and reflect on their work every week, thereby enhancing their learning by keeping the track of self-awareness and reflection.

METHODOLOGY

Schunk (1989) in his pioneering work on SCT as a theoretical approaches of SRL, emphasized on

(a) the importance of the principles of SCT and more importantly on the

(b) active rather than passive learning of the students.

Motivated from this active learning approach, we have considered the two key players of SRL, i.e., the self-awareness and the reflection.

Self-awareness and reflection are critical components of SRL, enabling students to evaluate their progress, adapt their strategies, and adjust their social and environmental contexts to optimize learning. Despite their importance, there has been limited systematic research linking self-awareness with reflection and with "specific interventions".

STUDY DESIGN

Our study design, roots from the theoretical framework, as illustrated before, where SRL for academic learning is well demonstrated by Schunk and Ertmer (2000) (where they incorporated noteworthy studies in this domain). Based on these studies, it is evident that SRL and self-efficacy in academic learning can be enhanced with the aid of usefulinterventions. Our research methodology can be better depicted with the aid of **Figure 1**. These interventions of course vary, depending on the level of education (school, college or university) and the mode of education (manual or programming based). In all such cases, learners' understanding of their performance is really important and Schunk and Ertmer (2000) commented on this important fact in following words:

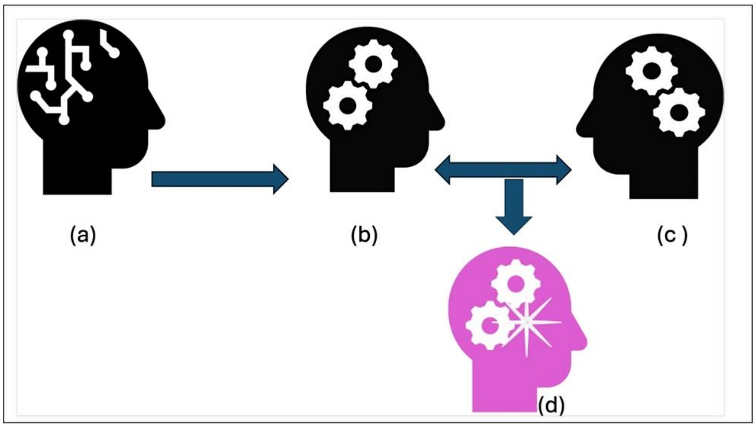

Figure 1. Schematic illustration: (a) irregular performance towards regulation, (b) through self-awareness and (c) the phase of reflection (c), and (d) to illuminate thoughts for improved thinking (Source: Authors' own elaboration)

> Learners obtain information about their self-efficacy from their performances, vicarious (observational) experiences, forms of persuasion, and physiological reactions. Students' own performances offer reliable guides for assessing self-efficacy.

In a nutshell, we have taken SRL as a key aspect of meta-cognition, during this research, and for SRL, we focused on

(a) self-awareness and then

(b) reflection phases.

Student's were provided maximum support to "support" their self-awareness and to improve their self-efficacy during this process of learning. This was achieved by maintaining e-portfolio.

Special consideration was given to students who failed to attempt the computer algorithms and computational mathematics programs, based on the following quote by Zimmerman and Ringle (1981):

> Successes raise efficacy and failures lower it.

The study aims to investigate the impact of self-awareness and reflection on student performance through a quantitative, discrete analysis. During this research, we have focused on the SRL process, specifically by examining how structured self-awareness and reflective practices contribute to improved academic outcomes. To infer (predict) the reflection successfully, we have used the Bayesian inference strategy for the given discrete problem.

Participants

The study had 150 students for university year 3 level of computational mathematics.

Self-Awareness

The study design of SRL was divided into two phases, the first phase of self-awareness had a focus on strengths and weaknesses of student's programming skills. The e-portfolio was designed, and each student's performance metrics were documented, every week, throughout the semester of 13 weeks. This record helped the students to analyze the debugging processes. It further helped them to avoid error and developed familiarization to the syntax. As an outcome their programming abilities were improved.

The concept of e-portfolio was interfaced to the "dynamic" user manual. By this we mean to say that based on the student's unsuccessful attempts, the basic coding commands were simplified by the instructor and the difficulty level of the exercises were modified according to the e-portfolio record.

As a result, each week's learning contributed to improving the learning interest and efficacy of the students and although the difficulty level increased week by week, but so did the successful attempts of students due to their self-awareness, making this meta-cognitive study successful.

Reflection Phase

The thought process behind learning and the integration of experiences during the first phase helped to develop a clearer picture of reflection of their learning. Reflections on overall learning experiences and what was learned from each assignment, project, or task were maintained by students and support was provided by the staff to maintain this information through their e-portfolio. Discussions on the understanding of key programming concepts and how knowledge has evolved over time helped the learners to further improve their reflection week by week. Students were able to approach the problems, to develop the strategies and to overcome the challenges due to their ability to see their performance's reflection.

Further to this, the self-awareness metrics and reflection scores were used together as patterns to develop a Bayesian inference protocol. This helped us to assess the reflection in future, based on the data of the self-awareness.

Table 1. Performance metrics for coding attempts for a preliminary test experiment of the study

Student	Successful attempts	Unsuccessful attempts	Time taken to debug (minutes)	Error frequency
1	5	2	30	3
2	4	3	45	2
3	6	1	25	1
4	3	4	60	4
5	7	0	20	0
6	2	5	55	5
7	5	2	35	2
8	4	3	40	3
…	…	…	…	…
150	3	4	50	4

Table 2. Quantitative measurement of student reflection

Student	Depth of thoughts	Insightfulness	Connection to learning outcomes
1	2	3	2
2	1	2	1
3	3	3	3
4	2	2	2
5	3	1	2
6	1	1	1
7	2	2	3
8	3	2	1
…	…	…	…
150	2	1	3

Outcome Measurement

The approach that we used during this study helped to develop deeper insights into learning processes, it also helped the students to connect theory to computer-based exercises and strengthened continuous improvement.

RESULTS

To measure success quantitatively from self-awareness and reflection in advanced programming courses, we have used discrete probability mass functions (PMFs) and Bayesian inference approaches.

Self-Awareness

We tracked performance metrics for the number of successful vs. unsuccessful coding at- tempts, the time taken to debug, and the frequency of specific errors throughout the semester via e-portfolio.

For example, a preliminary coding exercise was given to all the students. After correctly attempting a question, next question to be solved by same algorithm appeared on the computer screen. If a student made a mistake, the mistake along with a solutionappeared on the screen to help them be aware of their weakness(es). Their performance along with their experience of their improved self-awareness were recorded on the e-portfolio. A total number of seven questions appeared in a test exercise and the students metrics are shown in **Table 1**.

In a similar manner, records for all their performances were maintained throughout the semester and the PMFwas used to plot their self-awareness as an outcome of this learning process.

Reflection

In our study, reflection was measured quantitatively using a scoring system based on pre- defined criteria (1 = poor, 2 = average, and 3 = excellent). After completing a lab task, students were asked to reflect on their performance and learning experience. They self-assessed their performance (reflections) based on the depth of their thoughts (that also included self-awareness of their programming skills that they gained with practice), the insights gained, and how well their reflections connected to the learning outcomes of the task, as shown in **Table 2**.

Bayesian Inference

Let us examine the study of SRL as an uncertain domain, by this, we mean to say that the nodes of our study (self-awareness and reflection) are random variables, and the edges of this network represents the conditional probability for the corresponding states. Thus, we have now projected SRL to a Bayesian network.

Here by uncertainty we mean to say that the likelihood of the relationships between the two nodes of self-awareness and reflection may be uncertain since it varies from student to student, based on their cognition and thus meta-cognition.

Propagation of evidence

Next, we have designed the probabilistic inference. This approach can help the researchers to infer the

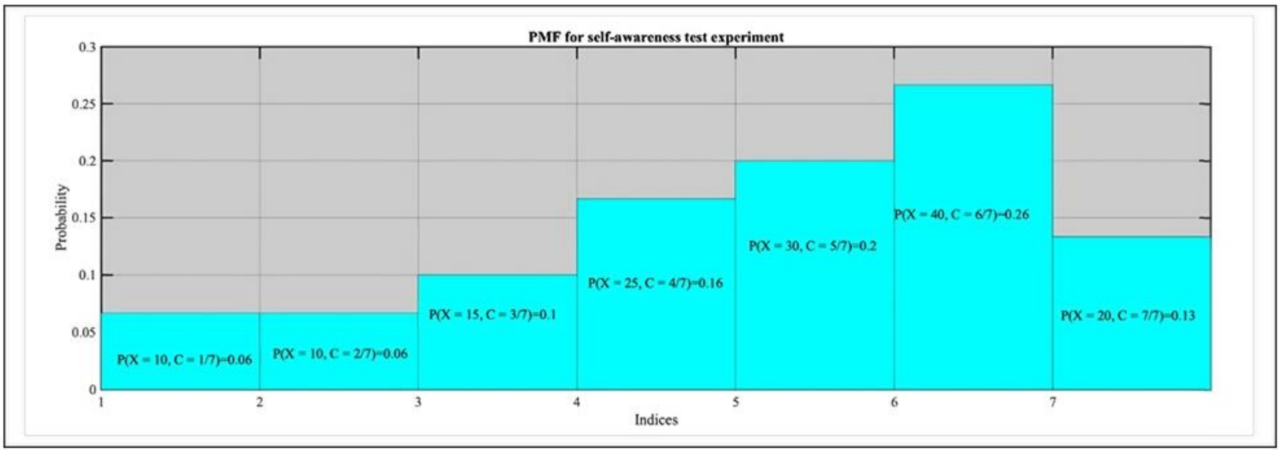

Figure 2. Probabilities of attempting one to all seven questions successfully (Source: Authors' own elaboration)

(a) propagation of the effect of evidence in our network and

(b) estimating the impact of this effect on the unknown variable(s), while the evidence propagated with time as the evaluations were updated at the end of each week throughout the semester.

In simple words, by knowing the values of the earlier step of our study, i.e., self-awareness, we can estimate the posterior probability of reflection.

Understanding the inference

Mainly, there are two branches of Bayesian inference, the single query inference and the multiple inference. During this research, we have focused on multiple inference. There are two subbranches of multiple inference,

(a) most probable explanation, where all non-observed variables are the subject, and

(b) maximum a posteriori (MAP) probability, where not all but some non-observed variables are the subject.

For the successful implementation of this learning to learn approach, we have executed the experiments and collected data for self-awareness and reflection and have used Bayesian inference to infer the results that were not predictable from the data.

To define the formula for MAP, we have first defined the probability function. Sincethe nature of our data is discrete, i.e., we collected students responses for each step, in discrete format, we have used the PMF. For example, the PMF for students responses for experiment detailed before was evaluated for each step, i.e., when the students made a single successful attempt to when they solved all the questions successfully. These results are presented in **Figure 2**. Here the indices refers to responses to seven attempts. In simple words, the first bar from left indicates the probability that 10 out of 150 students attempted only one out of seven questions successfully. Their process of learning from their mistakes was slow. Going towards right, we can see that 40 students of 150 attempted 6 out of 7 questions successfully as they rapidly learnt from their mistakes and improved, whereas there were 10 students who never made any mistake and attempted all the seven questions correctly. We observed a nice pattern of self-awareness and most importantly for the worst cases, we observed that for some students, it was hard to avoid mistakes even while using e-portfolio and similarly for best cases, where students maintained their performance.

By analyzing e-portfolios, where students reported their success and failures, the time they took to grasp specific idea and to translate the mathematical problem to programming language we received valuable record for our study. Learning programming languages from a conceptual perspective in a fear-free environment can lead to more promising results. With appropriate knowledge of syntax and loops, and the ability to translate mathematical iterative processes to algorithms, learning conceptually guarantees creativity and success.

Reflection Using Maximum A Posteriori Probability

To obtain reflection Y using the MAP probability given self-awareness X, we consider nine levels of self-awareness and here definition of these levels is more generalized as compared to preliminary test example presented above before and **Figure 2**, note that the level of satisfaction with self-awareness of the course ranged from 10% to 100% and then there were three levels of reflection: low, medium, and high, denoted as Y = {low, medium, high}. Let P(Y) represent the prior probabilities of these reflection levels: $P(Y = Y_i) = p_i$ for $i \in$ {low, medium, high}. Assume the following likelihood function based on awareness X:

$$P\ (X = x_i|Y_i) = p_{ij} \text{ for } x_i \in \{x_1, x_2, \cdots x_n\}, Y_i \epsilon \{low, medium, high\}. \quad (1)$$

Posterior calculation

Given an observed awareness $X = x_j$, the posterior probability of $Y = Y_i$ is $P(Y = Y_i \mid X = x_i) \propto P(X = x_i \mid Y = Y_i)\ P(Y = Y_i) = p_{ij} \times p_i$.

The posterior probabilities can be normalized, as follows:

Table 3. Posterior probabilities and MAP decision

X = xᵢ	P(X|Y =low)	P(X|Y =medium)	P(X|Y =high)	P(Y = low|X)	P(Y = medium|X)	P(Y = high|X)	MAP decision
10%	0.6	0.1	0.3	**0.5455**	0.1909	0.2636	Low
20%	0.5	0.2	0.3	**0.4545**	0.2818	0.2636	Low
30%	0.4	0.3	0.3	0.3529	**0.3824**	0.3824	Medium
40%	0.3	0.4	0.3	0.2727	**0.3650**	0.3650	Medium
50%	0.2	0.6	0.2	0.2000	**0.6667**	0.6667	Medium
60%	0.2	0.5	0.3	0.1739	**0.6522**	0.6522	Medium
70%	0.2	0.4	0.4	0.2222	0.3333	**0.4444**	High
80%	0.1	0.2	0.7	0.1538	0.3077	**0.5385**	High
90%	0.3	0.3	0.4	0.1667	0.1667	**0.6667**	High

$$P\left(Y = Y_i \middle| X = x_j\right) = \frac{p_{ij} p_i}{\sum_k p_{kj} p_k}. \quad (2)$$

MAP Estimate

The MAP estimate Y^{MAP} is the value of Y that maximizes the posterior probability:

$$Y^{MAP} = \arg max_{Y_i} P(Y = Y_i | X = x_j). \quad (3)$$

In this framework, we maximize the posterior P(Y|X) to determine the most likely level of reflection given the observed awareness.

As shown in **Table 3**, in the first column, the level of satisfaction with self-awareness of the course ranged from 10% to 100%, reflecting a measure of their perceived understanding and engagement. Next, the likelihood probabilities by utilizing Eq. (1) are provided in columns 2-4, and after using Eq. (2), the posterior probabilities are provided in columns 5-7, and finally the decision of whether the reflection of this level of satisfaction was low, medium or high, is provided in the last column by using Eq. (3).

Analysis of Results

In analyzing the data, we observed that for x_1 = 10% and x_2 = 20%, the level of satisfaction with self-awareness of the course was relatively low. Despite this, when considering the reflection outcome, it was also noted to be low (as shown in last column). This suggests that for these groups of students, the reflective practices within the course may not have been as effective in enhancing their self-awareness or perceived understanding. However, for x_3 = 30%, where the level of satisfaction was improved, the reflection outcome was observed to be medium. This indicates a potential correlation between satisfaction with self-awareness and the perceived effectiveness of reflective practices, suggesting that students who were more satisfied with their self-awareness also found the reflective activities or assessments to be more beneficial.

Attaining 100% satisfaction with one's self-awareness is often considered unattainable in practical scenarios (Silvia & O'Brien, 2004). Therefore, in our analysis, we have capped the level of satisfaction for self-awareness at 90%, which aligns with common expectations and observations.

DISCUSSION

Our study applied a Bayesian inference model to connect the nodes of self-awareness to reflection, essential components of SRL. When combined with SCT, this model was implemented on advanced-level mathematics students. These students were enrolled in courses where programming was a mandatory component of each mathematical approach.

Initially, both students and instructors found the process challenging, as evidenced by some students' responses. It reflects the observation made by Shane's (2014), that students find abstract concepts difficult to integrate in computational mathematics. Despite of these preliminary challenges, the study found that majority of students enjoyed this learning process. Our observations were similar to Akram and Li (2024) that the students' enjoyment has always been a major concern to keep them motivated and actively engaged , especially in challenging courses like mathematics. Considering this, teachers should incorporate interactive learning activities to keep students engaged and motivated throughout the course, such as collaborative projects, gamified learning modules, and real-world problem-solving tasks.

Moreover, the implementation of e-portfolios was found instrumental in fostering self- awareness among students. Through the use of e-portfolios, students were able to communicate, record their mistakes, and track their progress. Howell (2021) also noted that reflective learning practices allow students to manage their cognitive load by meticulously monitoring their progress. Similarly, Kholid et al. (2022) emphasize the role of reflective learning practices in improving their problem-solving skills. Therefore, educational institutions should make e-portfolios an important part of the curriculum and train students to effectively use it to track their progress. The results also showed that students responded to the same problem in new ways by engaging in a series of events, questions, and algorithm development. This approach affirms Rich et al. (2024) claim that good problem-solving skills are necessary in computational mathematics and Syzdykova et al. (2021) consider e-portfolio a critical step in bridging the gap between theory and practice in higher education. In this regard, students should be encouraged to adopt iterative approach by providing case studies or real-life problems to strengthen their problem-solving skills. The findings further emphasize a positive impact of iterative nature of the interventions and feedback on students' self-awareness leading to an improved reflection process each week with a better understanding of their learning journey and progress. The importance of self-regulation skills in academic success is also emphasized by Järvelä et al. (2023). It is thereforevital for concerned bodies to organize training sessions to enhance reflection and self-awareness skills among students. In addition, teachers should provide regular opportunities for reflection during instructional practices to reinforce these skills.

Conclusively, by utilizing the Bayesian inference framework for discrete datasets to connect the nodes of self-awareness and reflection, our study has laid a solid foundation for future research in this domain. Overall, our study was successful and offers useful in- sights for other educators and students by highlighting the importance of self-awareness in computer-based learning. By encouraging students to reflect on their performance through e-portfolios, we observed a positive impact on their self-confidence. This approach not only removes shyness but also builds confidence, as students can see their progress over time and actively participate in their learning journey.

CONCLUSIONS AND FUTURE WORK

In conclusion, this study underscores the critical role of SRL in enhancing students' academic outcomes and metacognitive skills. By focusing on SRL strategies, educators can empower students to take control of their learning process, leading to deeper conceptual understanding and improved performance. The application of Bayesian inference in educational research has demonstrated its potential to model complex learning processes and provide valuable insights into individual student needs. Integrating Bayesian methods into educational practices can lead to more personalized and effective learning interventions, ultimately enhancing student outcomes.

Moving forward, it is essential for university mathematics education to focus on developing students' problem-solving abilities and conceptual understanding. By employing interactive teaching methods and integrating technology, such as AI and virtual reality, educators can create engaging learning environments that cater to diverse learning styles and promote continuous improvement in mathematics education, especially for programming- based courses. This research aligns with the scope of examining the psychological impact of SRL on individuals using computer-based courses, particularly in applied mathematics, and contributes to understanding human behavior in the context of computer use, particularly in educational settings.

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Ethical statement: The authors stated that appropriate consent was obtained from the institution from which the educational performance data was collected, and it has been assessed to have minimal risk for participants. The authors further stated that the study was conducted after taking informed consent from the participants and to ensure the study adhered to ethical standards and minimized risks, the identities of the participating students were anonymized throughout the research. Further details can be obtained from the corresponding author.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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