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A conceptual SRLbot model for higher education based on Zimmerman's Self-Regulated Learning model

Mô hình khái niệm SRLbot cho giáo dục đại học dựa trên mô hình Học tập tự điều chỉnh của Zimmerman

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Abstract

This study presents an SRLbot model to transform Zimmerman's Self-Regulated Learning (SRL) model, in which learners set goals, monitor progress, and conduct self-evaluation, into an AI chatbot-assisted interactive model. Building from the SRL foundation, the SRLbot animates three core functions: planning, monitoring and reflecting, thereby prompting learners to set SMART (Specific, Measurable, Achievable, Relevant, and Time-bound) goals, to create deadline alerts and to conduct success-failure analysis. The SRLbot encourages the learner's ability to reason and control the learning process, it also personalises the experience through immediate responses and real-time learning data tracking that increases the student's autonomy. Initial results within a university-level educational context indicate that students using the SRLbot tend to maintain their motivation, actively engage in the learning process and achieve higher proficiency compared to those using self-adjustment learning methods only. AI integration into the learning experience offers the potential to enhance higher-order thinking skills by engaging students with a "virtual learning partner" who is always willing to reply to questions.

Keywords: self-regulated learning; AI chatbot; SRLbot; higher education; personalised support.

Tóm tắt

Nghiên cứu này giới thiệu mô hình SRLbot nhằm chuyển hóa mô hình Học tập tự điều chỉnh (Self-Regulated Learning - SRL) của Zimmerman, trong đó người học tự thiết lập mục tiêu, theo dõi tiến trình và tự đánh giá, thành một mô hình tương tác có sự hỗ trợ của chatbot trí tuệ nhân tạo (AI). Dựa trên nền tảng của thuyết SRL, SRLbot vận hành ba chức năng cốt lõi: lập kế hoạch (planning), giám sát (monitoring) và phản tư (reflecting). Qua đó, công cụ này thúc đẩy người học thiết lập mục tiêu theo tiêu chí SMART (Cụ thể - Specific, Đo lường được - Measurable, Khả thi - Achievable, Liên quan - Relevant, và Có thời hạn - Time-bound), tạo cảnh báo thời hạn và thực hiện phân tích kết quả học tập thành công hay thất bại. SRLbot khuyến khích năng lực suy luận và khả năng kiểm soát quá trình học tập của người học, đồng thời cá nhân hóa trải nghiệm thông qua phản hồi tức thì và theo dõi dữ liệu học tập theo thời gian thực, từ đó tăng cường tính tự chủ của sinh viên. Kết quả ban đầu trong bối cảnh giáo dục đại học cho thấy sinh viên sử dụng SRLbot có xu hướng duy trì động lực, tham gia tích cực vào quá trình học và đạt trình độ cao hơn so với nhóm chỉ áp dụng các phương pháp

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học tự điều chỉnh truyền thống. Việc tích hợp AI vào trải nghiệm học tập cho thấy tiềm năng nâng cao kỹ năng tư duy bậc cao, nhờ tạo điều kiện cho sinh viên tương tác với một "đối tác học tập ảo" luôn sẵn sàng phản hồi mọi thắc mắc.

Từ khóa: học tập tự điều chỉnh; chatbot AI; SRLbot; giáo dục đại học; hỗ trợ cá nhân hóa.

1. Introduction

Self-Regulated Learning (SRL) is a process through which students actively control their learning by setting goals, planning activities, implementing learning strategies, and reflecting on achieved outcomes by themselves. [34] concept is defined as a cyclical model consisting of three main elements: 1) forethought, 2) performance, and 3) self-reflection, creating a feedback loop that helps students optimize learning. In higher education, SRL is a recognized and accepted method since these learners must monitor their own time and resources within an autonomous learning environment. Sitzmann & Ely [28]'s study, through meta-analysis, indicates that SRL affects academic performance with a significant effect size (effect size = 0.55), confirming its role in enhancing self-management skills and developing the student's ability to learn. SRL is not just a learning method; it's a set of cognitive and metacognitive skills that help students adapt to complex academic requirements [23].

The literature indicates that SRL may have direct effects on academic performance of students by supporting the ability to complete learning programs through self-regulation of goals and the renewal of learning motivation in a cyclical manner. According to Pintrich and De Groot [23], SRL explains about 40% of the differentiation in final exam results, showing a close relationship between self-regulation and academic performance. Based on long-term studies, students who possess SRL skills tend to achieve better grades and have a 40% higher graduation rate compared to those without. This is attributed to how SRL encourages students to develop strategic cognition, maintain learning motivation and reinforce self-efficacy, thus overcoming educational challenges [23]. Additionally, Zimmerman [34]'s cyclical model posits that planning, monitoring processes and reflecting after each learning session helps students to adjust and adapt more suitable learning methods, leading to continuous improvements in their academic proficiency. SRL not only supports immediate success but also equips students with the essential skills necessary for lifelong learning, a crucial requirement in modern society [28].

True AI supported interactive technology is becoming popular and indeed, inseparable for self-regulated learning by providing personalised tools and real-time student-initiated interactions. For the purpose of this paper the term "AI-chatbot" or "chatbot" will be used in reference to this type of true AI technology. According to a survey conducted by Educause Center for Analysis and Research (2023), 65% of US universities are using or planning to use AI, including chatbot technology, to enhance student engagement and support student learning. Ng et al. [20]'s study indicates that due to chatbot's ability to provide personalised responses, while providing better ability to set goals and track learning progress, students who use AI chatbots experience a 20% increase in learning motivation and a 15% improvement in SRL skills compared to those who do not use them. This technology helps reduce academic stress and fosters sustainable learning habits with 70% of students reporting positive experiences using a chatbot program [8]. Furthermore, the personalised learning technology market generated revenue of $18.5 billion in 2023 and is expected to grow 15.2% each year until 2030 [26], with the educational AI segment, including SRL-supported chatbot, forecasted to reach $30.7 billion by 2028. This trend provides an insight into the confidence invested by educational institutions in the importance of SRL chatbots in learning and the future of education.

In recent years, the integration of AI chatbots in higher education has expanded administrative support to directly assist the learning process, especially fostering Self-Regulated Learning (SRL). Recent studies published show that chatbots can play a role as a scaffolding tool to help learners establish goals, track progress, and implement reflection after learning. These are the three key phases within the SRL model of Zimmerman [6; 10]. The personalization and instant response capabilities of chatbots have been demonstrated to increase students' motivation and engagement, even in large classroom settings [9; 11]. However, alongside these benefits, challenges remain, for instance, response accuracy, data privacy, and the need for adaptive interventions following learners' SRL level [19; 21].

While recent studies have demonstrated AI chatbot's effectiveness in personalising the learning experiences and enhancing learners' motivation, there is a gap in how these programs deliver SRL activities. Previous studies often lack clear theoretical frameworks when analyzing how SRL is operationalized in these chatbots, leading to difficulties in identifying variables at each stage, how learners transform their learning strategy, the SRLbot's role in such transformations, and an effective design to comprehensively assess the program's impact on the learning process as a whole. Therefore, this research suggests a new model for a SRLbot based on Zimmerman [34]'s cyclical model. Furthermore, it is suggested that other AI chatbot studies in education visualise the interaction of mechanisms and factors relating to academic performance enhancement through a more comprehensive application of SRL theory.

2. Literature review

2.1. Zimmerman's SRL cyclical model

Zimmerman's Self-Regulated Learning (SRL) cyclical model is a popular theoretical framework used in higher education, assisting students to manage their learning process actively and effectively. According to Zimmerman [34], SRL has three main stages: 1) forethought, 2) performance, and 3) self-reflection. At the forethought stage, students identify learning goals, set plans and evaluate their own capabilities as well as tasks' requirements, setting a foundation for a strategic learning process [35]. The performance stage focuses on applying learning strategies and progress tracking, in which students need to make flexible adjustments to enhance efficiency [27]. The reflection stage involves academic performance assessments, and lessons learned from successes or failures, thereby adjusting learning strategies for the next cycle [22]. Experimental research shows that students with good SRL skills tend to achieve better academic performance and develop higher-order thinking skills, especially in subjects requiring complex reasoning, such as mathematics and reading comprehension [4]. This model also emphasises the role of internal motivation as studies indicate that students with high motivation often use SRL strategies more effectively, stay focused on their goals and improve their academic performance [15]. In addition, emotion also affects SRL, with positive emotions enhancing perseverance and proactive learning engagement [29]. However, the effectiveness of the SRL model may be affected by cultural and personal contexts, requiring personalised teaching methods to optimise the result [14].

2.2. AI chatbot in higher education

AI chatbot integration in higher education is creating many opportunities for innovation, not only globally but also in countries like Vietnam. Anjulo Lambebo and Chen [3] affirmed that AI chatbots, particularly ChatGPT, have become an important tool to assist students in various fields such as information retrieval, concept explanation, programming support, and academic writing guidance. Groothuijsen et al. [7] also emphasised that due to its ability to respond quickly, correctly and flexibly, AI chatbots help students approach knowledge more conveniently, as well as fostering self-learning abilities and encouragement of critical thinking. In the Vietnam context, Duong et al. [5] indicated that factors such as performance expectations, effort expectations, and the level of knowledge sharing significantly affect intentions to use chatbots in learning. These findings are consistent with Abdaljaleel et al. [1]'s research, in which perceived usefulness and ease of use are the key drivers motivating students to adopt AI technology. AI chatbots not only help students find information effectively but also assists in personalised learning experiences providing a better fit for the individuals' needs and capacities. Rejeb et al. [25] showed that AI chatbots are contributing to reshaping teaching methods in universities. This technology assists teachers in designing lectures, providing instant feedback, and facilitating flexibility for students to access extended learning resources. Therefore, the integration of AI into teaching not only enhances learning outcomes but also increases student engagement and interest in the course content. This is particularly important in modern education as integrated and online learning models continue to evolve. Apart from academic support, AI chatbots are also widely applied in providing educational management and student services. According to Thottoli et al. [30], many universities have applied AI chatbots to support courses providing: advising, course registration guidance, financial information and advice, and career counselling. Because these programs can operate continuously, AI chatbots ease the burden on student support departments, further optimizing operational processes in educational institutions. In Viet Nam, Duong et al. [5] identified that student interactions with ChatGPT, assisted them to obtain academic materials, to practice writing skills, and to improve foreign language proficiency. The research demonstrates that this technology helps students gain diverse knowledge while creating more flexible and personalised learning opportunities.

Recent systematic reviews have classified chatbot functions into the phases of the SRL cycle. In the forethought phase, chatbots assist learners in setting goals and planning using recommendations and personalised notifications [10; 17]. In the performance phase, the chatbot provides instant feedback and recommends learning resources to help them self-track and adjust their strategies [9; 11]. Finally, in the self-reflection phase, conversational factors guide learners in evaluating their results and aligning their learning plan for the future [6]. Although these benefits have been documented, synthesis studies also emphasize that the long-term impact on SRL skills requires personalised and consistently sustained interventions [9; 21].

3. Methodology

This study adopted a theoretical synthesis method combined with document analysis to propose a conceptual model, "SRLbot", based on the traditional foundation of Self-Regulated Learning (SRL) [23; 34]. The process of searching and selecting literature was designed following a simplified PRISMA approach to ensure replicability. First, the search process was conducted across databases including Scopus, Web of Science, and Google Scholar that have limited publications from 2010 to 2025 with priority of studies published in 2023-2025 to ensure recency. The searching keywords followed the Boolean string below:

("self-regulated learning" OR "SRL" OR "self regulation" OR "self-regulated learner*") AND ("chatbot" OR "AI chatbot" OR "artificial intelligence" OR "conversational agent" OR "generative AI") AND ("higher education" OR universit*university* OR "college student*")

In addition, the study conducted backward and forward citation tracking from foundational SRL works (e.g., Zimmerman, 2000) and recent systematic reviews on AI-supported SRL (e.g., Guan et al., 2025 [8; 9]; Huang & Hew, 2025 [11]).

Inclusion criteria consisted of: (1) context of higher education or upper secondary education; (2) conceptual, review, or empirical studies with a clear connection between chatbot AI functionalities and SRL phases (forethought - performance - self-reflection); (3) peer-reviewed publications in English; (4) publication year ≤ 2025. Exclusion criteria included: commentaries not based on SRL frameworks, studies involving chatbots outside educational contexts, and duplicate records.

The screening process involved two stages: (1) title and abstract screening to retain 170 documents; (2) full-text review to select 38 studies meeting all inclusion criteria. Specifically, in stage (1), the documents were screened based on their titles and abstracts. Only studies addressing at least two of the three main themes (self-regulated learning, AI chatbots, and higher education contexts) were retained, resulting in a total of 170 eligible records. In stage (2), all 170 records were reviewed in full text and assessed against the inclusion criteria. This process reduced the dataset to 38 studies that were most relevant to the research topic, all of which fully satisfied the criteria. Thus, the final dataset consisted of 38 studies used for analysis.

For each document, data were extracted, including bibliographic information, research design, SRL phases addressed, chatbot functions (planning - monitoring - reflection), learner-related variables, and key findings.

The synthesis of findings was performed using a narrative-comparative approach. First, the research team identified core components of the three-phase SRL cycle [23; 34] and examined the interplay of motivational, time-management, and self-monitoring factors [28] within academic settings. Next, the traditional SRL model was compared to the chatbot AI's findings published [18; 20] that emphasize the functions of goal suggestion, assignment reminders, and real-time feedback to support learning cycles This research compared these findings with those of Guan et al. (2024) [8] and with the recognized limitations of AI research. From this comparison, the core aspects to be integrated into the SRLbot model were identified.

The consistency of the theoretical framework allows for a clear identification of the three-phase SRL construct and analysis of chatbot function (planning - monitoring - reflection) to ensure the consistent interaction between "learners" and "AI". In addition, the research considers the relationship between motivation, technology familiarity, and learner performance, as well as the sociocultural and technical conditions proposed by Torre & Daley (2023) [31]. The results of the document analysis help position the SRLbot model within the research stream of self-regulated learning with self-assessment elements, while also identifying gaps that AI tools may address, particularly in strengthening the quality of reflection.

4. Suggested model for better SRLbot learning outcomes

4.1. SRLbot - AI chatbot that assists SRL

SRLbot is an AI chatbot specifically designed to promote Self-Regulated Learning (SRL) in higher education, specifically to enhance learning autonomy through setting goals, providing personalised responses and tracking learning progress [24]. SRLbot significantly heightened motivation and improved academic performance, as demonstrated by students using ChatGPT or Q-Module-Bot often developing sustainable study habits, with reduced stress, and improved self-assessment processes [2]. The SRLbot strength lies in its ability to personalise the learning experience by using AI to adjust content and responses according to individual needs, thereby making it easier for students to understand their progress while adjusting their learning strategies [33]. Studies also prove that students interacting with SRLbot tend to achieve better academic performance attributed to continuous assistance and more effective self-assessment [12].

4.2. AI chatbot integration according to each SRL stage

The SRLbot model inherits the three-stage cycle of SRL [34] (figure 1), including forethought, performance, and self-reflection, but adds some chatbot features (Planning feature (PLF), monitoring feature (MF), Reflection feature (RF) to enhance the effectiveness of self-regulated learning. Additionally, six key variables related to learners (Internal Motivation (IM), Technology Familiarity (TF), SRLbot Interaction (SI), Self-Time Management (STM), Satisfaction with SRLbot (SS), Self-Evaluation (SE) are included to explain how students interact with AI tools and their impact on Goal Quality (GQ), Academic Performance (AP), Reflective Quality (RQ) and Post-Reflection Motivation (IM_post). This approach creates an integrated SRL loop, in which SRLbot usage provides a continuous support channel, ensuring that learners are no longer "alone" but have additional AI resources to strengthen their motivation and are more likely to engage higher-order thinking skills [20].

4.2.1. Forethought stage

At the forethought stage, Zimmerman [34]'s original model emphasises the role of Internal Motivation (IM) and student belief in personal capacity. In the SRLbot context, the Planning Feature (PLF) is the central tool that allows learners to set SMART goals as well as structure their learning strategies. PLF effectiveness depends on Technology Familiarity (TF) and Internal Motivation (IM) since students with high technological proficiency and strong motivation tend to access PLF more easily and establish Goal Quality (GQ) more clearly [32].

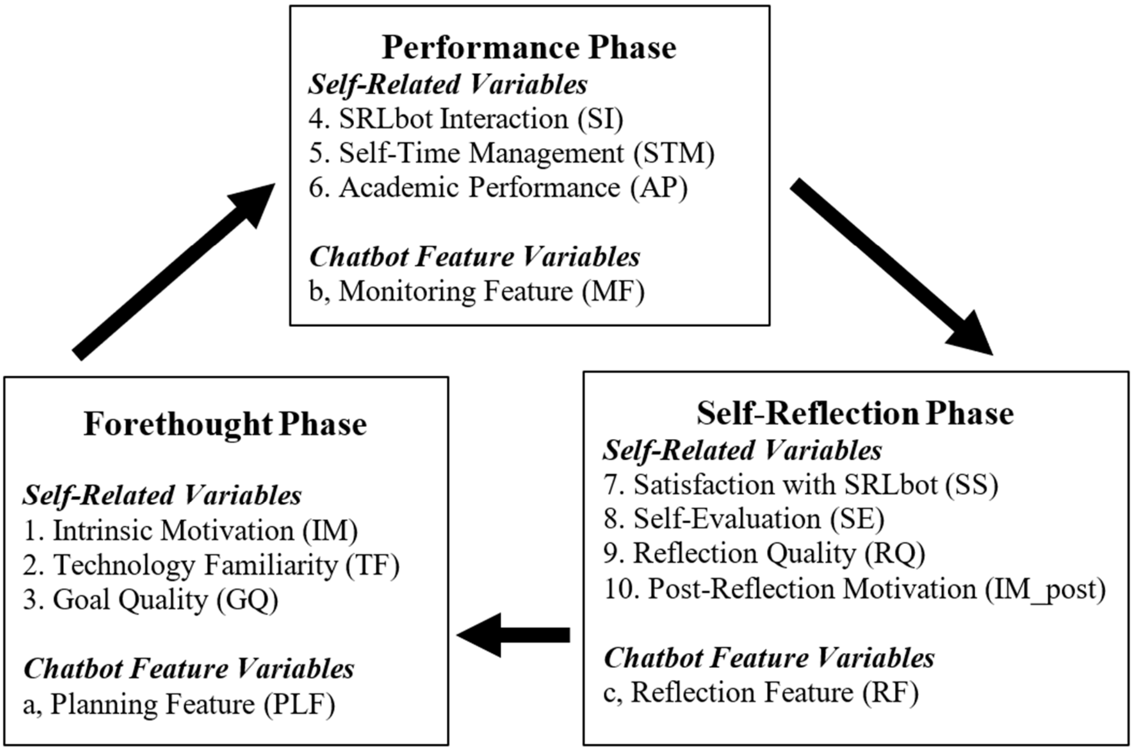

Figure 1. The proposed Self-Regulated Learning (SRL) model integrating SRLbot across all three cyclical phases (adapted from Zimmerman, 2000)

4.2.2. Performance stage

At the performance stage, Zimmerman [34]'s model demands learners to maintain Self-Control and Self-Observation. The SRLbot model suggests using a Monitoring Feature (MF) to examine progress, to remind students of deadlines and to suggest timely strategy adjustments. The ability to take advantage of the MF is determined by the SRLbot Interaction (SI) and the Self Time Management (STM). When SI is high, students continuously respond and update notifications, and when STM is strong, learners can effectively manage their study time. Consequently, Academic Performance (AP) may be greatly enhanced by MF, which supports real-time monitoring of the learning process [16].

4.2.3. Self-reflection stage

The Self-reflection stage in Zimmerman [34]'s model includes Self-Judgment and Self-Reaction. As for the SRLbot, the Reflection Feature (RF) provides automatic performance analysis, asks suggestive questions and proposes a roadmap for future adjustments. The Satisfaction with SRLbot (SS) and the Self-Evaluation (SE) are two variables that determine the extent to which learners utilise the RF since high SS and SE will promote in-depth analysis and enhance the Reflection Quality (RQ). Furthermore, results obtained in this stage affect Post-Reflection Motivation (IM_post), which encourages learners to return to the planning stage for the next learning cycle and feeds back to the use of the Planning Feature (PLF) [8].

Table 1. A brief comparison between the original model from Zimmerman (2000) and the suggested SRLbot model and classification of roles by the entities at each stage (Learners - AI Chatbot)

Stage	**Original model from Zimmerman (2000)**	**SRL model with SRLbot participation**	
		Self-Related Variables	**Chatbot Feature Variables**
Forethought	Task Analysis: Goal Setting, Strategic Planning Self-Motivation Beliefs: Self-Efficacy, Outcome Expectations, Intrinsic Interest/Intrinsic Value, Goal Orientation	1. Intrinsic Motivation (IM) 2. Technology Familiarity (TF) - Possible to measure learners' readiness and enthusiasm, as well as their ability to use technology to exploit PLF. 3. Goal Quality (GQ) - Usually measured at the end of the planning phase but still reflects the “outcome” of the learner's planning.	1. Planning Feature (PLF) - Chatbot suggests setting SMART goals and making initial strategies based on learners’ needs and context.
Performance	Self-Control: Self-Instruction, Visualisation, Attention Focus, Task Strategy Self-Observation: Process Logging, Self-Monitoring	4. SRLbot Interaction (SI) 5. Self-Time Management (STM) - Indicators of students monitoring, completing tasks, and continuously interacting with chatbot during the learning process. 6. Academic Performance (AP) - Possibly measured as results or progress at the end of the performance stage.	2. Monitoring Feature (MF) - Chatbot tracks progress, sends deadline reminders and suggests strategy adjustments during the performance stage.
Self-Reflection	Self-Judgment: Self-Assessment of Results, Attribution of Causes Self-Reaction: Self-Satisfaction/Affect, Adaptation/Protection	7. Satisfaction with SRLbot (SS) 8. Self-Evaluation (SE) 9. Reflection Quality (RQ) 10. Post-Reflection Motivation (IM_post) - Reflects learners' perceptions of chatbot experience, its ability to assess learning outcomes, and the motivation shift to initiate the next SRL cycle.	3. Reflection Feature (RF) - Chatbot analyses performance, prompts guiding questions, and suggests adjustments for learners to self-assess and reflect on their experiences.
SRL Loop	Emphasises the continuous cycle between the three stages to optimise the self-regulation process.	RQ and IM_post foster PLF return for the next cycle.	

5. Discussion

The study suggests an SRLbot model based on Zimmerman [34]’s SRL framework and cites on preliminary results of the application of AI chatbots in higher education. The integration of the three main features, including planning support, monitoring and reflection, demonstrates the potential to significantly enhance the student self-regulated learning process by providing personalised feedback, maintaining motivation, and improving self-assessment abilities. Learner-related factors such as Intrinsic Motivation, Technology Familiarity and Self-Time Management are proven to have decisive roles in effectively exploiting chatbot features, from pre-planning to self-reflection [20]. Importantly, previous studies indicate that when students positively interact with a chatbot, they tend to develop more sustainable learning habits, maintain longer interest and gain better academic performance [12]. Furthermore, the presence of a support tool like a SRLbot encourages the learner's active role in the self-regulation process; it inspires deeper thinking about goals, strategies, and performance, thereby clarifying the cognitive and metacognitive mechanisms that are fundamental to SRL [35]. Indeed, SRL theory anticipated some of the most useful qualities of AI in terms of its ability to cycle quickly to fuel the interest of the student or to change tactics if the interest of the learner begins to fade. The consistent failure of education has always been the limited ability to adjust content, pace and style to accommodate different learning styles, a SRLbot is designed to do that while providing affordable, open, and flexible access.

Considering the practical aspect, SRLbot model is expected to help reduce the burden on instructors in tracking progress and reminding students while enhancing personalisation for learners through the implementation of multiple functions such as suggesting SMART goals, deadline reminders, and asking questions to analyse success/failure of a learning session. However, it is still necessary to acknowledge that the effectiveness of the model may be influenced by the learning context, technical resources, and the users' readiness to adopt technology [13]. Moreover, AI chatbot's nature still has some limitations in giving correct responses that require vigilant students or risks regarding data security for students, requiring universities to establish a clear monitoring process and policies [32]. These issues signal that SRLbot integration is no longer simply a technical issue but also one of harmonisation of education policies, of the development of ethical guidelines, and creation of processes to protect privacy and intellectual property.

Recent studies highlight several strengths in integrating chatbots into the SRL framework. Most notably, chatbots' ability to personalise and provide instant responses enhances learners' dependence and reduces assessment workload for instructors [9; 11]. In the context of Vietnamese higher education, where large class sizes and high lecturer-student ratios persist, partially automating the learning support process may shorten the distance to response and progress monitoring. However, limitations must also be considered, including the reliability of chatbot-generated feedback, potential risks related to data privacy, and the need to calibrate chatbot functions to match the diverse SRL proficiency levels of students [17; 21]. In addition, AI governance policies in Vietnam remain in their early stages, so the pilot implementation must be accompanied by clear guidelines about privacy, mechanisms for informed consent, and structured training programs on digital/AI capability for both students and lecturers.

Future research can explore empirical testing of the SRLbot model in diverse environments, such as online learning, traditional classroom or blended learning applications. Studies that compare the use of a SRLbot with those who do not will help to quantify the model's impact on academic performance, as well as test hypotheses regarding the model's effect on motivation, performance, and quality of self-reflection. Another possible improvement in AI features might be for chatbots to record learners' emotions, thereby adjusting responses in real time and enhancing the model's adaptive abilities [16]. Moreover, building big data storage about learning behaviours will allow SRLbots to self-improve, identify learners' difficulties early and provide timely strategic adjustments. These research directions not only help to complete the model but also contribute to SRL theory development as AI technology reshapes higher education [8].

The SRLbot model, currently developed in this study, can serve as a theoretical foundation for pilot implementation or expansion of chatbot features in university settings. Researchers may choose to fine-tune any part of the model, such as adjusting the scale for interaction with SRLbot, integrating the metacognitive awareness scale for a more accurate assessment of the reflection process, or further investigating psychological factors such as academic anxiety and creative interest. This action will not only help to authenticate the SRLbot model but also opens opportunities for interdisciplinary collaboration between educational technology, psychology, and educational management.

6. Conclusion

This study was built on past research and suggested an SRLbot model that integrates three SRL stages of Zimmerman [34] with planning, monitoring, and reflection features for an AI chatbot platform, and clarifies the role of individual variables such as motivation, technology familiarity, and self-time management in an effective implementation of a SRL model. While the model proposed in this paper has not been fully verified through empirical experimentation, theoretical arguments and initial survey results demonstrate significant potential in enhancing learning quality, maintaining motivation, and promoting the student self-regulation processes through the use of this SRLchatbot.

There are apparent limitations to this study. First of all, the applications of an AI chatbot are likely to encounter barriers if the technological infrastructure is not sufficiently stable or if the information security policies are not well-developed [13]. Secondly, SRLbot's personalisation depends on the richness and accuracy of the training data, requiring further research to ensure that the chatbot is flexible enough to provide guidance for learners of different proficiency levels [20]. Thirdly, the model's effectiveness may be affected by differences in culture, teaching methods and learner psychology, making it difficult to generalise results on a larger scale [32].

Despite its limitations, the suggested SRLbot model represents a step forward in connecting SRL theory and AI technology, clarifying how students can utilise a virtual partner to enhance cognitive skills, develop structured learning and planning habits, continuously monitor progress, and engage in AI-prompted deep self-reflection. The model presented in this paper can be used as a critical step toward more in-depth research on self-regulated learning in ongoing digital transformation of higher education, while also inspiring the development of more integrated learning support systems in the future.

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