UTM UNIVERSITI TEKNOLOGI MALAYSIA
INTERNATIONAL JOURNAL OF INNOVATIVE COMPUTING
ISSN 2180-4370
Journal Homepage : https://ijic.utm.my/

Exploring Explainable AI and Reinforcement Learning in Educational Conversational Agents with Metacognitive Self-Regulated Learning: A Systematic Literature Review

Li Haoze*, Noraini binti Ibrahim, Chan Weng Hoe, Muhammad Luqman Mohd Shafie, Shahliza Abd Halim & Nor Azizah Saadon
Faculty of Computing
Universiti Teknologi Malaysia
Johor Brahru, Malaysia
Email: lihaoze@graduate.utm.my

Submitted: 15/9/2025. Revised edition: 28/11/2025. Accepted: 5/1/2026. Published online: 28/7/2026
DOI: https://doi.org/10.11113/ijic.v16n1-2.683

***Abstract*—This systematic literature review explores integrating conversational AI, reinforcement learning (RL), and interpretable AI (XAI) in programming education to enhance metacognitive self-regulated learning (MSRL). Conversational AI offers programming support and feedback, and combining it with RL optimizes interaction strategies, yet existing studies suffer from overreliance on generative AI, insufficient long-term empirical evidence, and AI "black box" issues. XAI, while addressing the black box problem, struggles to balance performance and interpretability. Core research questions include effective RL integration for MSRL, XRL's role in building trust, conversational AI's support for code generation and metacognitive training, application challenges, and long-term experiment design. A"conversational AI+RL+XAI+affective computing" framework was established via database searches, with mixed methods analyzing quantitative and qualitative data. Findings reveal a focus on paired technology combinations rather than overall synergy. Key challenges are mismatched XAI interpretation strategies, difficulty quantifying MSRL as RL rewards, and lack of standardized evaluation. The study fills critical research gaps, providing a foundation for transparent adaptive educational AI. Future research should prioritize process interpretability, large-scale long-term teaching experiments, and optimized multi-objective reward functions to advance programming education tutoring systems.**

***Keywords*—Reinforcement learning, Explainable Artificial Intelligence, Metacognitive Self-Regulated Learning, Conversational AI**

I. INTRODUCTION

In the current era of deep penetration of artificial intelligence technology into the field of education, explainable artificial intelligence (XAI) has become a key support for solving the "black box" dilemma of AI and promoting the compliant application of technology in educational scenarios, especially in programming teaching for IT majors in higher education, where its value is becoming increasingly prominent. The core logic of XAI is "people-oriented", which means that when generating explanations, it is necessary to fully adapt to the needs and task scenarios of specific stakeholders (such as programming learners). However, existing research has shown that most XAI technologies currently do not meet expectations in helping users understand the working principles of AI, establish trust, and assist decision- making [1].

In the context of programming education, XAI's core value focuses on empowering students with metacognitive self- regulated learning (MSRL). By making AI's decision-making logic transparent, providing dynamic feedback and personalized explanations, XAI can guide students from "passively receiving code answers" to "actively planning learning paths, monitoring learning processes, and reflecting on learning problems" in the MSRL mode.

From the current practice status of MSRL, AI agents have become an important auxiliary tool for IT students' programming learning - students can obtain targeted answers by submitting questions and requirements to AI agents. But to truly enhance students' MSRL abilities, relying solely on AI output results is far from enough. AI also needs to clearly present its thinking and problem-solving process, which is the core function of XAI. Currently, some students lack trust in XAI and have low satisfaction with its output results, believing that it cannot meet their learning expectations. This situation highlights the shortcomings of XAI in the application of MSRL in programming education.

The current academic community has attempted to integrate reinforcement learning (RL) into conversational AI to dynamically adapt to the personalized needs (such as knowledge gaps) and preferences (such as interaction rhythms) of programming learners. However, there is a key gap in existing research: the lack of a comprehensive framework covering the interpretability of MSRL in software programming scenarios. In programming education, learners can only effectively carry out the "plan monitor reflect" cycle of MSRL, establish trust with AI, and achieve efficient collaboration by understanding the logic behind AI suggestions, such as the reasons for code errors and the basis for learning path recommendations.

Therefore, the core question of this study focuses on how to organically integrate RL technology with conversational AI to enhance MSRL technology in software programming education? At the same time, how to solve the problem of insufficient interpretation quality of existing language models in XAI? This issue involves both technological integration and innovation, as well as the specificity of educational scenarios and the actual needs of learners.

This study aims to fill the research gap of "using conversational AI to enhance programming education MSRL", promote the integration of RL and interpretable technology, and provide theoretical and practical basis for designing a "transparent and adaptive educational conversational AI framework"; Simultaneously exploring the usability of chatbots embedded with MSRL technology, evaluating their ease of learning and use through user satisfaction surveys.

Exploring interpretable technologies in RL-MSRL design: For the scenario of RL driven conversational AI supporting programming education MSRL, screen and optimize adapted interpretable technologies (such as feature attribution and decision logic visualization), clarify how to make AI coaching strategies (such as code debugging suggestions and learning plan recommendations) understandable, and lay the foundation for subsequent system integration.

Integrating XAI technology to build a feedback mechanism library aligned with MSRL: embedding XAI technology into RL conversational AI environment to generate a feedback mechanism library covering the entire stage of MSRL-planning stage explaining learning path recommendation basis, monitoring stage disassembling code error logic, reflecting stage summarizing learning problem patterns, ensuring that AI feedback is accompanied by clear explanations.Experimental verification and effectiveness evaluation: Conduct experiments through multiple types of programming tasks (basic syntax, error debugging, project development), recruit learners with different programming backgrounds to participate in testing, and evaluate the actual effectiveness of the framework from two dimensions: "programming skill performance" (code correctness, debugging efficiency) and "metacognitive behavior" (planning rationality, reflection depth).

The significance of this study lies in multiple dimensions: at the knowledge level, it fills the research gap of "RL+conversational AI supporting MSRL interpretability" and enriches the theoretical system of the intersection of educational AI and metacognitive learning; On a practical level, provide a feasible technical path for the development of programming education AI tools, directly serving teaching scenarios; On an ethical level, guide the responsible application of educational AI to avoid trust crises caused by "black box decision-making"; At the educational level, promote the transformation of programming education from "passive knowledge transmission" to "active MSRL", and assist in the innovation of computing education. Research on the Integration Mechanism of RL and XAI Technologies. Explore how to combine the strategy update mechanism of reinforcement learning with interpretability models to enable AI to self optimize based on student feedback during the response process. Build a feedback mechanism library covering the three stages of MSRL, including Plan ,Monitor, Reflect)

A multi technology fusion framework of "conversational AI+RL+XAI+affective computing" was constructed by combining metacognitive self-regulated learning and reinforcement learning theory. By using natural language processing to ensure smooth interaction between conversational AI and students, emotional computing technology helps students overcome frustration and achieve dual regulation of emotions and cognition

II. LITERATURE REVIEW

With the development of large language models (LLMS) and conversational AI, programming education is undergoing profound changes. Traditional programming teaching relies on Teachers' teaching and students' self-study, while the introduction of conversational AI enables students to obtain instant feedback, debugging help and learning path guidance in natural language interaction [2]. This not only improves learning efficiency but also shows great potential in personalized learning and metacognitive self-regulation.

Many studies have shown that the dialogic system based on LLM such as chatgpt can help students generate and debug code and reduce the difficulty of getting started. For example, this one found that in the process of interacting with AI, students can not only generate runnable code but also improve their understanding of algorithm logic through dialogue [3].

In recent years, more and more research has focused on the application of dialogic AI in intelligent tutoring system to simulate the human teacher's questioning, feedback and guidance functions. It developed a personalized conversational programming tutoring system, which has effectively improved learning motivation and programming performance in programming courses for beginners [4].

Conversational AI not only acts as an individual learning assistant, but also shows its application potential in group cooperative learning and teacher teaching feedback. It emphasize the role of AI as a "team member" in teacher training and curriculum design, which can provide a new support mode for educational design [5].

The core essence of explainable artificial intelligence is to map the mathematical decisions of artificial intelligence into a logical process that humans can understand, which corresponds to the original intention of the research to make up for the metacognitive self-regulation learning in conversational artificial intelligence enhanced software programming. Research in the field of XAI focuses on improving user confidence, trust, satisfaction and transparency. Researchers have learned that interpretability evaluation should focus on XAI 's fixed effects, such as trust, transparency, understandability, usability, and fairness [6]. In software programming education, it is important to understand the use of XAI tools by learners and embed reinforcement learning technology in chatbots to help metacognitive self- regulation learning. Explore the usability test of learners for chatbots embedded with metacognitive self-learning technology. The usability standard can be measured by investigating the user satisfaction of users using chatbots embedded with metacognitive self-regulation technology, and by ease of learnability, ease of use, efficiency and effectiveness.

As the accuracy of machine learning models increases, the opacity of their decision-making process becomes a problem [7]. The commonly used ChatGPT is like a 'black box', with its internal decision-making process being opaque to users, which may raise questions about the fairness and reliability of AI generated results, especially in high-risk educational scenarios such as grading, coaching, or evaluation [8]. Thus, the field of XAI came into being.

Interpretable artificial intelligence provides relevant machine learning techniques to enable language models to be more understood and trusted by users [9]. In the field of education, explainable artificial intelligence has provided great help in improving the transparency and decision assistance of intelligent systems [10]. Integrated explainable artificial intelligence enables the teaching process to better understand AI decisions, thereby achieving the goal of promoting the educational process [11]. In addition, interpretable artificial intelligence can help doctors better diagnose patients' conditions by improving the interpretability of medical diagnostic models, providing more explanatory diagnostic and therapeutic evidence [12]. Adequate protection is also provided for vehicle safety in vehicle system assurance [13].

In the teaching process of students, it is crucial to cultivate their MSRL, which is essential for educators who understand the online learning environment [14]. Understanding metacognitive self-regulated learning is an important process for learners to plan, monitor, and control cognition and behavior, and to improve students' metacognitive self-regulated learning and enhance the usability of the learning process [15]. About interacting with chatbots, students are able to better plan their learning and set higher performance goals [16]. In addition, chatbots, as AI tools, support students' learning through personalized feedback and immediate finteracting withps stimulate and support the SRL process [15]. The comparison between student-generated explanations and AI-generated explanations can promote metacognitive reflection [17]. Self-learning is very important for students in the learning process. By adding XAI, students can be more effectively helped to conduct metacognitive self-regulation learning. In response to the current situation, metacognitive self-regulation learning is an important part of programming education. In the future, it will focus on implementing explainable and scalable artificial intelligence in the field of education, providing a series of guarantees for educators [10].

Large language models such as conversational artificial intelligence provide assistance in generating computer code, but accuracy needs to be improved. Therefore, the implementation of XAI is even more important [18]. Large language models applied in education have shown positive effects in improving students' learning process and acceptance, but they still need to be improved in detecting false statements and providing accurate responses. Future research should explore more advanced fact-checking mechanisms and consider the use of more cost-effective language model options [19]. As shown in the Fig. 1 about RL+XAI+ MSRL Integration Pathway.

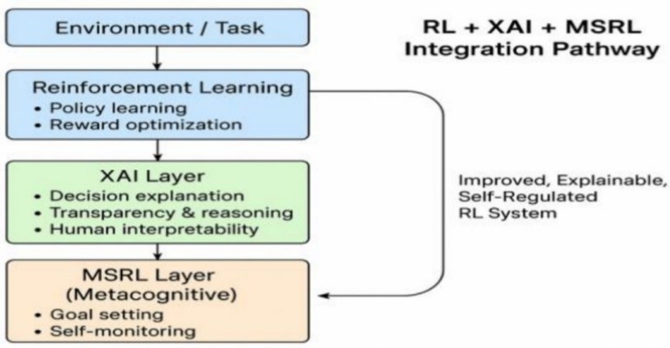

Fig.1. RL+XAI+ MSRL Integration Pathway

III. METHODOLOGY

This content revolves around the integration of AI technology to assist metacognitive self-regulated learning (MSRL) in programming education, clarifying five core research questions. The literature is sourced from relevant academic indexes and journals, using MSRL and RL as theoretical frameworks and combining NLP, affective computing, and XAI to determine search logic. Relevant research is screened to construct a "conversational AI+RL+XAI+affective computing" fusion framework. A mixed research method is also planned to collect quantitative and qualitative data to analyze the effectiveness of the system and its impact on the learning experience.

A. Identify Research Questions

1) How can reinforcement learning (RL) be effectively integrated into programming education to support metacognitive self-regulated learning (MSRL) processes such as planning, monitoring, and reflection?

2) What role can interpretable reinforcement learning (XRL), which combines explainable AI (XAI) and RL, play in enhancing trust and controllability for teachers and learners?

3) In what ways can dialogue-based AI systems, such as ChatGPT, assist students in code generation, debugging, and fostering metacognitive awareness through self-monitoring and reflection prompts?

4) What challenges remain in applying conversational AI and XRL to programming education, particularly regarding interpretability, learner understanding of AI decision logic, and optimization of long-term learning paths?

5) How can future research design long-term experiments in real teaching contexts to validate the effectiveness of integrating XAI, RL, and conversational AI for supporting MSRL?

B Select Literature Repositories

The literature review of this article is sourced from academic indexes and journals of various universities. Table 1 show the selected academic database. Table2 below shows the classification of key points in the literature review. Fig. 2 show the PRISMA-style digram

TABLE 1. THE SELECTED ACADEMIC DATABASE

Online repository	***Reason for selection***
IEEEXplore	A database under the Institute of Electrical and Electronics Engineers (IEEE), the world's largest repository of scientific and technological literature in the fields of electronic information and computer science.
Scopus	The world's largest comprehensive academic database, covering multiple fields such as natural sciences and social sciences, with a focus on citation analysis and scholar evaluation.
Web of Science (WoS)	A comprehensive database that covers high-quality academic literature from multiple disciplines and has powerful citation indexing capabilities, providing key support for researchers to search for literature, analyze academic trends, and evaluate research impact.

TABLE 2 THE CLASSIFICATION OF KEY POINTS IN THE LITERATURE REVIEW

Class	***Core theme***	***Representative literature***	***Methodology/data sources***
Education AI and intelligent tutoring sytems	Intelligence tutoring, conversation agent, metacognitive support	[4]	Experimental research, classroom intervention, theoretical framework
Application of generative AI in education	Chat GPT, LLM, curriculum design programming teaching	[3] [5] [19]	Two years of teacher feedback, code evaluation, university case
Can Explain AI(XAI) in Education	Learning analysisinterpretation, trust assessment, transparency	[6] [10] [11]	Experiment, student perception survey, review
AI ethics and privacy	Ethical challenges and privacy protection of AI in education	[7] [8] [20]	Literature review, case study, data interpretation
AI acceptance and learning effectiveness	TAM model, SRL support, course experience	[14] [15] [16]	Mixed methods, questionnaires, master's thesis
Academic writing and educational technology	Scientific writing, the state of AI in education	[18] [21]	Guidelines articles, systematic reviews

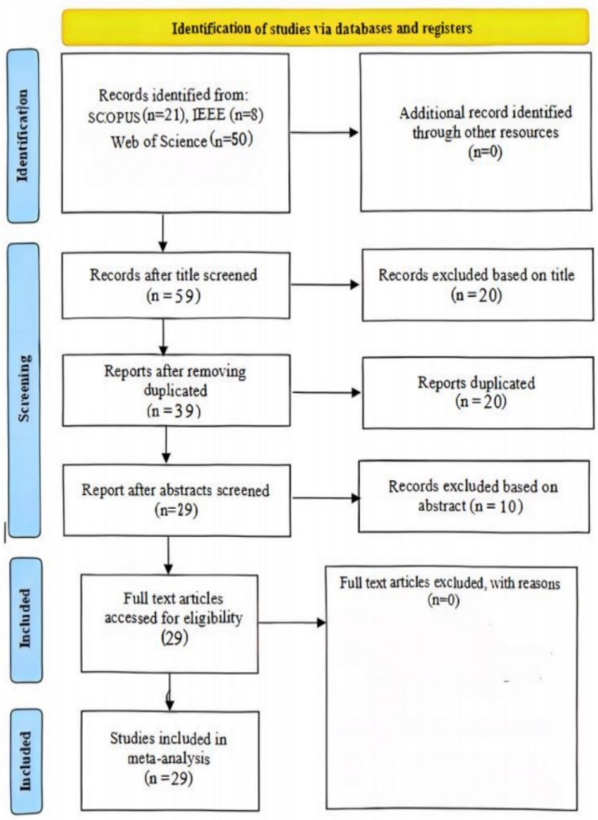

Fig.2. The PRISMA-style digram

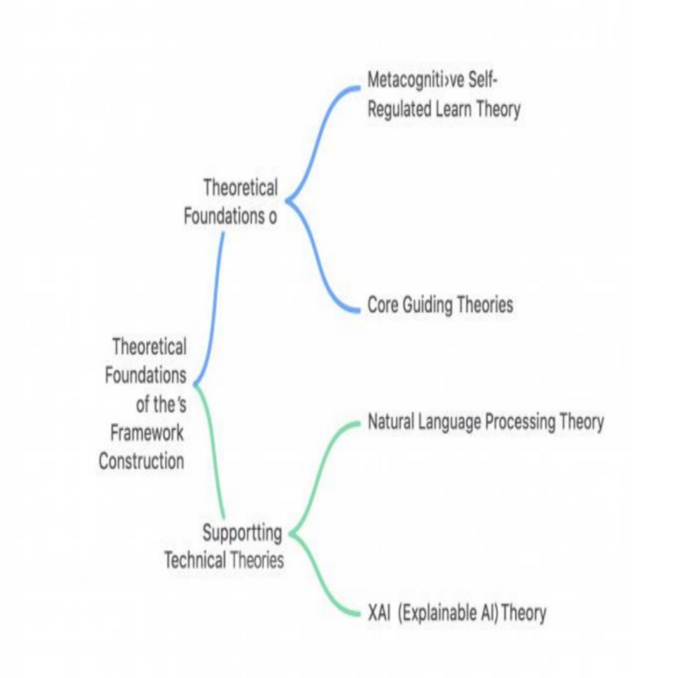

Fig.3. Theoretical Foundations of the Study Framework Construction

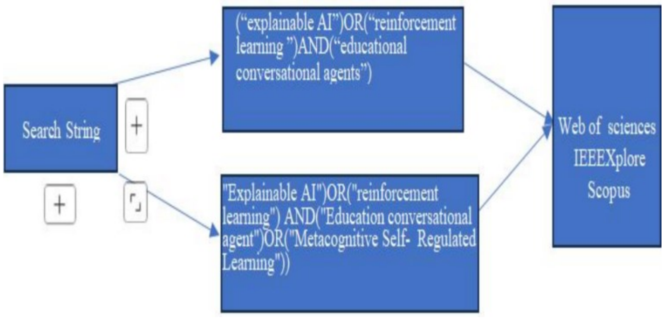

Fig.4. Displayed relevant literature sources

C. Indentify the search string

Using metacognitive self-regulated learning and reinforcement learning as theoretical frameworks, combined with natural language processing. Play the core role of metacognitive self-regulation in learning. Providing a basis for designing conversational AI intervention strategies, such as triggering student related behaviors through AI to strengthen metacognitive awareness; The trial and error feedback optimization mechanism of reinforcement learning theory provides technical principles for conversational AIto dynamically adapt to student states, driving AI to adjust support strategies based on student performance; Natural language processing technology ensures smooth interaction between conversational AI and students, as well as effective real-time feedback; Emotion computing theory supports AIto achieve emotion recognition and support, helping students over come frustration and achieve dual regulation emotions and cognition; The XAI theory provides ideas for solving the "black box" problem in RL and enhances the transparency of system decision-making. As shown in the abrove Fig. 3. Fig. 4 displayed relevant literature sources.

D. Selection ofthe related studies

Build a multi technology fusion framework of "conversational AI+RL+XAI+emotional computing". Build a conversational AI architecture with LLM as the core to achieve code assistance, real-time feedback, and metacognitive prompts; Introducing RL into the framework, with student programming error rate, reflection frequency, and other state variables, and improving metacognitive ability as the reward goal, dynamically adjusting AI support strategies; Design an explanation module based on XAI, using natural language and visualization to illustrate the decision-making basis of AI; Embedding an emotion computing module to recognize students' emotions through text analysis, providing dual regulation of emotions and cognition.

Developing an exclusive dialogue model based on LLM fine-tuning, integrating programming education corpus to enhance scene adaptability; Adopting the Coggen framework to integrate student modeling with generative AI, recognizing learners' metacognitive states through data-driven approaches, and implementing personalized interventions through RL; Drawing on the MetaTutor system, combining RL with metacognitive strategy training, dynamic reflection and monitoring prompts are added to conversational AI, and the intensity of prompts is adjusted according to students' abilities.

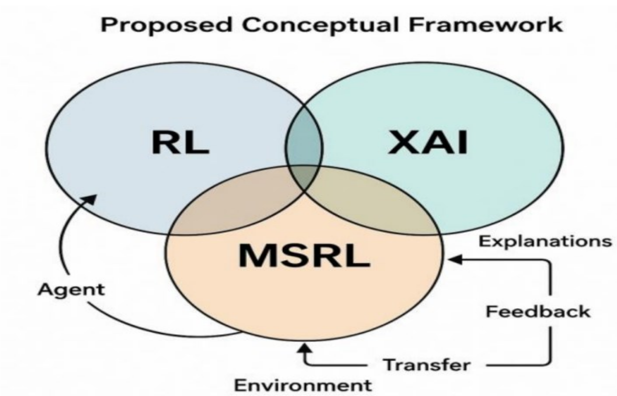

Fig. 5. A summarizing diagram of the proposed conceptual framework to show the RL + XAI + MSRL integration pathway

E. Synthesis and extraction ofthe data

Plan to collect quantitative data (programming error rate, learning duration, metacognitive ability scale scores, etc.) and qualitative data (interaction logs, interview records, teacher evaluations, etc.). Using a mixed research method, quantitatively analyze the differences between students before and after using the system through statistical methods, verify the system's effectiveness, and optimize model parameters; Qualitative analysis encodes data through thematic analysis, extracts themes of changes in students' metacognitive behavior, and analyzes the impact of system related functions on learning experience. As shown in the above Fig. 5. Provide a summarizing diagram of the proposed conceptual framework to show the RL + XAI + MSRL integration pathway.

IV. CONCLUSION

This study focuses on software programming education scenarios and revolves around Conversational AI enhanced metacognitive self-regulated learning (MSRL). The core focus is on addressing the "black box" problem of reinforcement learning (RL) and the application integration of explainable artificial intelligence (XAI). The detailed content and research contributions are as follows:

Traditional programming education heavily relies on teacher-student interaction, while conversational AI can provide real-time feedback, code assistance, and metacognitive prompts (such as ChatGPT and other large language model systems), and RL can also achieve dynamic adaptation through trial and error optimization. However, the opacity of RL decision-making weakens teacher-student trust, and existing research lacks large-scale long-term experiments and personalized mechanisms, making it difficult to support the complete process of "planning monitoring reflection" in MSRL. This situation has become the core entry point for research.

At the theoretical level, the research focuses on MSRL and RL theories, integrating natural language processing, sentiment computing, and XAI theory to construct a multi technology integration framework. This framework provides systematic theoretical support for the intervention strategy design of conversational AI (such as metacognitive prompts), dynamic adaptability (RL based interaction optimization), and transparency enhancement (cracking the "black box" through XAI), filling the theoretical fragmentation problem of a single technology supporting MSRL in programming education.

The research has identified the limitations of the current field: insufficient interpretability of RL leads to trust barriers, and there is a lack of optimization mechanisms for long-term learning paths. Based on this, its core contributions are reflected in the uniqueness of problem focus. For the first time in programming education scenarios, the combination of conversational AI enhanced MSRL and RL "black box" cracking, XAI integration, and targeted solutions to trust and adaptation issues in technical applications. The Innovation of Theoretical Framework which constructed multi technology integration framework provides interdisciplinary theoretical support for conversational AI in intervention strategies, dynamic adaptation, and transparency enhancement, connecting the gap between MSRL theory and AI technology applications.

The Feasibility of the practical plan is the developed integrated system and hybrid research method provide empirical evidence and technical prototypes for the design of adaptive and interpretable AI systems in programming education, verifying the effectiveness of the "RL+XAI+affective computing" collaborative support for MSRL. About the guidance for future directions, Propose a future path of deepening "process interpretability" technology, conducting large-scale long-term experiments, and optimizing multi-objective reward functions (balancing short-term support and long-term planning), providing clear research coordinates for the development of the field.

In summary, this study not only fills the theoretical and practical gap in integrating AI technology to support MSRL in programming education, but also provides a key theoretical basis and practical reference for the design of adaptive and interpretable programming education intelligent systems.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Universiti Teknologi Malaysia (UTM) for the opportunity and continuous support in carrying out this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

REFERENCES

[1] Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., ... & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, 100074. https://doi.org/10.1016/j.caeai.2022.100074

[2] Tilak, S. (2025). *A cybernetic guide to implementing artificial intelligence for collaborative learning: A synthesis of four studies conducted with adult learners*. ResearchGate.

[3] Enman, A., & Hassan, S. (2025). *From code to competence: Assessing LLMs' ability to generate and improve code*. Uppsala University.

[4] Alrobai, A., & Cristea, A. I. (2025). Personality-aware conversational intelligent tutoring system with GenAI: Studying the effect on learners in introductory programming. In *Artificial Intelligence in Education* (pp. 450–463). Springer.

[5] Agostini, D., & Serbati, A. (2025). AI as a team member for educational design: School teacher feedback from a two-year study. In *EDULEARN25 Proceedings*.

[6] Brdnik, S., Podgorelec, V., & Šumak, B. (2023). Assessing perceived trust and satisfaction with multiple explanation techniques in XAI-enhanced learning analytics. *Electronics, 12*(12), 2594. https://doi.org/10.3390/electronics12122594

[7] Naretto, F. (2023). *Explainable AI methods and their interplay with privacy protection*.

[8] Mienye, I. D., & Swart, T. G. (2025). ChatGPT in education: A review of ethical challenges and approaches to enhancing transparency and privacy. *Procedia Computer Science, 254*, 181–190.

[9] Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., ... & Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. *ACM Computing Surveys, 55*(9), 1–33. https://doi.org/10.1145/3556558

[10] Rachha, A., & Seyam, M. (2023). Explainable AI in education: Current trends, challenges, and opportunities. In *Proceedings of SoutheastCon 2023* (pp. 232–239). IEEE.

[11] Idrizi, E. (2024). Exploring the role of explainable artificial intelligence (XAI) in adaptive learning systems. In *Proceedings of the Cognitive Models and Artificial Intelligence Conference* (pp. 100–105).

[12] Lee, S. Y.-T., & Ma, K.-L. (2024). HINTs: Sensemaking on large collections of documents with hypergraph visualization

and intelligent agents. *IEEE Transactions on Visualization and Computer Graphics*.

[13] Nwakanma, C. I., Ahakonye, L. A. C., Njoku, J. N., Odirichukwu, J. C., Okolie, S. A., Uzondu, C., ... & Kim, D. S. (2023). Explainable artificial intelligence (XAI) for intrusion detection and mitigation in intelligent connected vehicles: A review. *Applied Sciences, 13*(3), 1252. https://doi.org/10.3390/app13031252

[14] Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Aldraiweesh, A., Alturki, U., Almutairy, S., ... & Soomro, R. B. (2024). Extended TAM-based acceptance of AI-powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. *Heliyon, 10*(8). https://doi.org/10.1016/j.heliyon.2024.e29437

[15] Yadav, N. (2024). *Exploring the role of a chatbot in supporting self-regulated learning (SRL) among students with low and high SRL skills* (Master's thesis).

[16] Aksu Dünya, B., & Yıldız Durak, H. (2024). Hi! Tell me how to do it: Examination of undergraduate students' chatbot-integrated course experiences. *Quality & Quantity, 58*(4), 3155–3170. https://doi.org/10.1007/s11135-023-01772-2

[17] Li, W. (2024). *Understanding learners and the interplay between metacognitive judgements of learning and AI-generated explanations* (Doctoral dissertation).

[18] Meyer, J. G., Urbanowicz, R. J., Martin, P. C., O'Connor, K., Li, R., Peng, P. C., ... & Moore, J. H. (2023). ChatGPT and large language models in academia: Opportunities and challenges. *BioData Mining, 16*(1), 20. https://doi.org/10.1186/s13040-023-00339-9

[19] Neumann, A. T., Yin, Y., Sowe, S., Decker, S., & Jarke, M. (2024). An LLM-driven chatbot in higher education for databases and information systems. *IEEE Transactions on Education*.

[20] Adnan, M., Uddin, M. I., Khan, E., Alharithi, F. S., Amin, S., & Alzahrani, A. A. (2022). Earliest possible global and local interpretation of students' performance in virtual learning environment by leveraging explainable AI. *IEEE Access, 10*, 129843–129864. https://doi.org/10.1109/ACCESS.2022.3226188

[21] Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

.