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Theoretical models of AI in student-centered education: a systematic literature review

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ABSTRACT

The use of artificial intelligence (AI) in education has garnered heightened interest, particularly in facilitating student-centered learning. This research conducts a thorough evaluation of theoretical models and empirical investigations about the implementation of AI in secondary education from 2020 to 2025. The 15 high-quality publications were selected from the Scopus and Web of Science (WoS) databases according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) procedure and analyzed thematically. The findings indicated that the present incorporation of AI in education predominantly depends on 11 fundamental theoretical frameworks, such as self-determination theory (SDT), theory of planned behavior (TPB), technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), and sociocultural theory (SCT). For example, SDT emphasizes students' motivation and psychological needs, the TPB explains behavioral intentions for using AI, and TAM/UTAUT is used to explain students' willingness and behavior in using AI tools. However, the application of AI still faces numerous challenges, including anxiety and ethical dilemmas. This study clarifies the correspondence between theory and practice, providing a theoretical foundation for educators to conduct instructional design and support work, and offering a reference for policymakers to develop AI education standards and allocate resources.

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1. INTRODUCTION

In recent years, the significance of artificial intelligence (AI) technology in education has grown markedly, particularly in facilitating student-centered pedagogical changes [1]. The rapid advancement of AI technology is leading to its increasing application in education, particularly in facilitating student-centered learning. The student-centered education concept emphasizes that students influence the teaching method of learning content, activities, materials, and progress [2], and is also a teaching method that encourages teachers to provide differentiated support for students with different backgrounds. AI has enormous promise in customized learning, adaptive learning, human-computer interaction, and intelligent tutoring, in addition to revolutionizing how educators and students utilize digital technology [3], [4].

AI can provide customized learning plans based on individual characteristics, preferences, and performance metrics, thereby enhancing motivation, engagement, and creativity [1], [5], [6], productivity, educational outcomes, personalized instruction, and immediate feedback [7]. Moreover, Shrivastava *et al.* [8] contend that a principal advantage of AI in education is its ability to improve students' academic performance by enabling them to choose a learning method that corresponds with their own pace [9]. AI enhances students' communication abilities in language acquisition contexts [10]. AI-driven educational interventions can significantly alleviate anxiety in middle school students [11].

On the other hand, barriers to integrating AI into education are associated with literacy, pedagogy, and educational systems. High costs, a lack of teachers and professional training programs, and slow changes at the curriculum and academic structure level are all barriers to AI implementation [12]. The development of AI tools should be guided by a clear theory to ensure the application of educational technology [13]. The public, education practitioners, and policymakers have not yet fully recognized the substantial contribution of AI to improving the quality of education [12]. Thus, a deeper understanding of how AI integration impacts learning is necessary. In light of the worldwide digital revolution in education, the use of AI in the classroom has generated a lot of debate regarding moral principles and how they affect student learning in addition to increasing the efficacy of instruction.

The use of AI in education has been extensively examined in numerous thorough literature studies. Ambarita and Nurrahmatullah [14] analyzed the impact of AI on learning outcomes based on research distribution, education stage, and performance indicators. Sánchez-Prieto *et al*. [15] focused on the role of AI in learners' assessment, identifying three major areas: behavior, emotion, and performance assessment. Vargas-Murillo *et al*. [16] analyzed the application potential and ethical challenges of ChatGPT in higher education. In addition, Hashim *et al*. [17] focused on the practical path of AI in personalized learning and MOOCs, as well as technology and AI trends in personalized learning education.

To effectively integrate AI into educational practice, many studies have introduced various theories to explain students' behavior, motivation, technology adoption, and learning outcomes. Among them, the self-determination theory (SDT) believed that individuals stimulate intrinsic motivation and grow in learning by satisfying basic psychological needs such as autonomy and competence [18], [19]. For example, SDT has been widely used to explain how AI promotes student online learning engagement [20], learning motivation [21], and student autonomy [22]. The theory of planned behavior (TPB) is used to study the driving factors that affect students' generative AI [23]. Technology acceptance model (TAM) is used to study the determinants of students' use of AI systems [24]. Virtual reality educational media and innovative educational resources based on cognitive load theory [25].

Despite the increasing richness of related theories [26], it is emphasized that most existing reviews on AI education are qualitative analyses, with a small number of studies and a lack of comprehensive analysis of research topics and development trends. In addition, there is a lack of systematic integration between different studies, as well as a lack of discussion on the applicability of theories to student groups. This deficiency not only limits researchers' overall understanding of the mechanisms by which AI affects learning but also makes it difficult for educators and policymakers to make teaching or resource allocation decisions based on theoretical frameworks. To address this research gap, this study does not focus on a single theory, but rather integrates multiple theoretical frameworks through a systematic literature review (SLR), analyzing the complementary mechanisms of AI in supporting student learning, emotion regulation, and motivation enhancement from an intertheoretical perspective.

Therefore, this study identifies and integrates the main theoretical models used in AI education practice, and systematically summarizes the core directions of current theoretical applications and the development trend of cross-theoretical integration. Compared with previous studies focusing on single theories. This study provides a more systematic theoretical summary, which helps to form a more coherent theoretical foundation for future research in the field of AI education.

In this context, this paper aims to examine the integration path of AI in student-centered education through a SLR. Through a systematic analysis of high-quality empirical research in the past 5 years, this paper is committed to providing strong empirical support, theoretical foundation, and practical reference for future AI education research. To achieve this aim, the study addresses the following research questions:

- What are the core theoretical models of current AI-education integration? (RQ1)
- How do AI tools support functional positioning in student learning? (RQ2)
- What are the beneficial impacts of AI integration on student learning, and what challenges does it encounter? (RQ3)

2. METHOD

SLR is one of the most famous and popular methods, which is mainly used to assist in the effective retrieval, assessment, and interpretation of important works on a particular scientific topic [27]. It facilitates the monitoring of the fast advancement of scientific literature and enhances the comprehension of certain notions [28]. In this way, SLR can also help researchers identify gaps in existing research and potential innovations for future research [29].

Overall, SLR is a tool for identifying knowledge gaps, indicating methodological weaknesses, or shifting areas of focus to guide future inquiry in a solid and meaningful way [30]. This research adopted a SLR approach and used the preferred reporting items for systematic reviews and meta-analyses (PRISMA) to standardize the processes of identification, screening, eligibility, and inclusion. According to the guidelines highlighted in Page *et al.* [31] and the PRISMA statement, the use of automatic categorization software should be taken into account when choosing which studies to include in the systematic review. In this study, the researchers used Microsoft Excel as an internal tool.

According to Moher *et al.* [32], it is necessary to provide at least one database. This choice was considered reasonable based on the established quality standards, as the presence of at least two databases can avoid missing relevant studies [33]. Two well-known databases were used in this study: Web of Science (WoS) and Scopus, which are generally accepted as the most extensive bibliographic databases [34]. WoS is one of the first and most significant bibliographic databases, featuring a large collection. Journal selection, study assessment, and other duties are its traditional uses [35]. Unlike WoS, Scopus covers journals and conference articles in different subject areas [36]. To ensure the coverage and reproducibility of the search, this study selected WoS and Scopus as the primary databases. These two are the most widely used in systematic reviews and already provide sufficient core interdisciplinary literature; therefore, no other databases were included.

2.1. Identification

A keyword identification process was employed to enhance the effectiveness of the search strategy. The search string was constructed by using Boolean operators [27]. As shown in Table 1, the joining of the terms “AI” and “theory” using Boolean operators was intended to capture research related to AI and theory in secondary education. In the first stage of the systematic review, a total of 152 papers were retrieved from databases, including 88 from Scopus and 64 from WoS, of which 18 duplicate articles were excluded. Thus, a total of 134 articles were included.

Table 1. Search terms for the systematic review process

Database	Keyword used
WoS	(AI) AND (THEORY) IN SECONDARY EDUCATION
Scopus	(AI) AND (THEORY) IN SECONDARY EDUCATION

2.2. Screening

The screening process aims to ensure that the collected literature is highly pertinent to the subject of the study. The exclusion criteria refer to the fact that although some studies meet the inclusion criteria, they are excluded due to bias or methodological quality defects, which may impact the reliability of the research findings [37]. In addition, to ensure the quality of the literature, this study excluded conference papers and conference abstracts that had not undergone full peer review [38], as their reports were often not detailed enough. During the screening process, the selection criteria of the literature are based on the theme of this study and classified in combination with the research content related to AI and theory. According to the exclusion and inclusion criteria listed in Table 2, a total of 134 articles entered the second stage of screening, of which 32 articles that did not meet the criteria were excluded.

Table 2. Criteria for inclusion and exclusion

Criterion	Exclusion	Inclusion
Time period	2020 and earlier	Between 2020 and 2025
Literature type	Systematic review, books, conference proceedings, and meeting abstract	Research article
Language	Non-English	English
Publication stage	In press	Final

2.3. Eligibility

The third step involved 102 articles undergoing qualification evaluation. This stage is a manual screening procedure in which papers are included or omitted based on the authors’ criteria [39], [40]. The research group will carefully analyze the title, abstract, research question, and research results of each article to assess whether it matches the inclusion criteria and fits the study’s aims. Following examination, 87 papers were removed, primarily due to inconsistency in the research field, a mismatch in the research subjects, or an educational stage that did not suit the scope of this study. Finally, Figure 1 shows the detailed

PRISMA process, including the number of documents identified, screened, eligible, and included at each stage. A total of 15 kinds of literature passed the qualification review and entered the next level of review, as shown in Table 3.

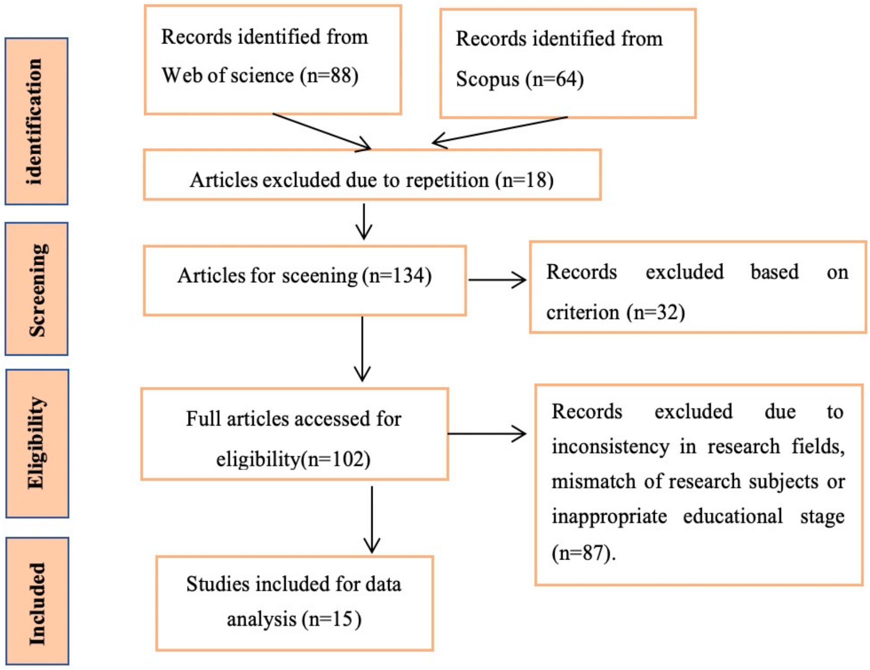

Figure 1. PRISMA diagram of the proposed searching study

Table 3. List of articles included in the SLR

No.	Author	Title	Year
1	Gupta *et al.* [41]	A teacher, a tutor, a friend: ChatGPT and the high school experience	2025
2	Ling *et al.* [42]	AI-generated content-supported collaborative rural mural creation: a training framework for university and school students, educators, and community members	2025
3	Dang *et al.* [43]	Deliberative interactions for socially shared regulation in collaborative learning: an AI-driven learning analytics study	2024
4	Okada *et al.* [44]	Fostering transversal skills through open schooling supported by the CARE-KNOW-DO pedagogical model and the UNESCO AI competencies framework	2025
5	Wu and Zhang [45]	Generative artificial intelligence in secondary education: applications and effects on students' innovation skills and digital literacy	2025
6	Chai *et al.* [46]	Modeling Chinese secondary school students' behavioral intentions to learn artificial intelligence with the theory of planned behavior and self-determination theory	2022
7	Ni and Cheung [47]	Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning	2023
8	Sing *et al.* [48]	Secondary school students' intentions to learn AI: testing moderation effects of readiness, social good and optimism	2022
9	Olugbade *et al.* [49]	Facilitating cognitive load management and improved learning outcomes and attitudes in middle school technology and vocational education through AI Chatbot	2024
10	Alghasab [50]	English as a foreign language (EFL) secondary school students' use of artificial intelligence (AI) tools for developing writing skills: unveiling practices and perceptions	2025
11	Wen *et al.* [51]	A study on the relationship between AI anxiety and AI behavioral intention of secondary school students learning English as a foreign language	2024
12	Xia *et al.* [52]	A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education	2022
13	Galindo-Domínguez *et al.* [53]	Using artificial intelligence to promote adolescents' learning motivation. A longitudinal intervention from the self-determination theory	2025
14	Janubas *et al.* [54]	Development of a Chatbot and evaluation of its effects on learning and intrinsic motivation of a public secondary school's Spanish language learners.	2024
15	Chai *et al.* [55]	An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn artificial intelligence	2020

2.4. Data analysis

This study used the data analysis method described in Salm *et al*. [56]. First, the quality of the selected articles (qualitative + quantitative + mixed methods) was assessed according to the mixed methods assessment tool (MMAT) 2018 version [57], and the five core quality criteria for each type were used. Two experts evaluated the articles based on the clarity of the research question, the confidence in the assessment of the research question, the rationality of the sampling strategy, the appropriateness of the data collection method, the appropriateness of the statistical analysis and how to interpret the data, and the presentation of the results, discussion and conclusions.

The thematic synthesis of this study focuses on the application and integration of AI in learners-centered education. To conduct a systematic data analysis, this study adopted the thematic synthesis method proposed by Thomas and Harden [58], which is widely used in systematic reviews of qualitative evidence. The analysis process is divided into three stages: i) coding the results of the included studies line by line; ii) developing descriptive themes based on the original research results, making them as close to the original research as possible; and iii) generating analytical themes, in which researchers summarize and sublimate the existing research to form new explanatory perspectives or hypotheses. To improve transparency and consistency, the research team used qualitative data analysis software to assist throughout the process.

Based on this, to improve reliability, the second and third authors randomly selected two articles (about 11%) for blind coding [59]. The Kappa coefficient [60] was used to measure the consistency between raters. A kappa value of 0.40 to 0.60 is regarded as average, 0.60 to 0.75 as acceptable, and 0.75 and higher as exceptional, under the evaluation standards [61], [62]. The two coders' consistency in classifying the articles in this investigation was κ=0.79. The differences were resolved through team discussion, and the final coding framework was created after reaching a consensus. Subsequently, the first author systematically coded all the included articles and gradually refined and integrated the results into three core categories: "theoretical models", "AI tools supporting functional positioning", and "beneficial impacts and challenges".

3. RESULTS

3.1. What are the core theoretical models of current AI-education integration?

Driven by the learner-centered educational philosophy, AI is becoming an important means to enhance learning motivation, autonomy, and personalized teaching experience. To guarantee the efficient integration of AI tools in education and to give full play to their educational potential, researchers have explored it from multiple theoretical dimensions. Through a systematic analysis of current literature, as presented in Table 4, this article summarizes existing research into the following five theoretical levels and supplements the theoretical integration trends and supplementary frameworks in recent years.

Table 4. Core theoretical models of AI-education integration

No.	Theoretical name	Representative literature	Application description
1	SDT	[46], [52]–[54]	It emphasizes that AI should improve learners' learning intention, involvement, and educational results by meeting their psychological needs and autonomous motivation.
2	TPB/extended theory of planned behavior (E-TPB)	[46], [48], [55]	It is used to reveal how students' perceptions, AI literacy, social values, and emotional factors jointly influence their behavioral intentions to learn AI.
3	Unified theory of acceptance and use of technology (UTAUT)	[51]	UTAUT, combined with AI anxiety theory, is used to reveal the impact of emotional factors on students' intention to use AI to learn English.
4	TAM/extended TAM (E-TAM)	[45], [47]	It used to predict learners' willingness to use AI tools and their usage behavior.
5	Cognitive load theory	[49]	Based on this theory, the role of AI chatbots in reducing students' cognitive burden and improving learning outcomes is evaluated.
6	Diffusion of innovations (DOI)	[45]	This theory explains the mechanism by which generative AI promotes the development of innovative ability and digital literacy in education.
7	Sociocultural theory (SCT)	[50]	Based on SCT, this paper explores how AI writing tools can act as an intermediary to promote students' writing development.
8	Constructivism	[42]	AI-generated content (AIGC) tasks guide students to actively construct knowledge and understanding in real cultural contexts.
9	Social - cultural learning theory	[42]	As a cultural intermediary, AIGC supports the joint construction of cultural identity and learning significance through multi-party collaboration.
10	Socially shared regulation in learning	[43]	Analyze students' shared behavior patterns of cognitive and emotional regulation in collaborative learning and their effectiveness differences.
11	Digital literacy development	[45]	Reveal the progressive development of students' multi-dimensional literacy abilities through active technology interaction in AI environment.

3.1.1. Motivation and behavioral intention theory

This theory emphasizes that satisfying the needs for proficiency, relatedness, and autonomy among students is the key to stimulating motivation to learn AI [63]. For example, previous research [46], [52]–[54] all stated that in the context of AI teaching, if students' psychological needs can be met through AI feedback and emotional support, as their participation increases, they may obtain more information, thereby generating intrinsic motivation to further learn AI. The TPB is used to explain the factors and behavioral intentions of students' willingness to adopt AI. Another research [46], [48], [55] proposed that students' attitudes towards AI, their perceived behavioral control, and subjective norms influence their intentions to engage in learning behaviors, particularly within AI courses and skill development contexts.

3.1.2. Technology adoption and acceptance theory

This type of theory focuses on how students accept and adopt AI tools, including TAM, UTAUT, and diffusion of innovation theory. Previous research [47], [45], [51] studied students' willingness and use of AI tools for learning based on E-TAM, TAM, and UTAUT models, respectively. Among them, research by Wen *et al.* [51] integrated UTAUT with AI anxiety theory and found that students' anxiety levels had a major influence on their willingness to use AI tools, and proposed the need to strengthen emotional regulation mechanisms and teacher support. In addition, Wu and Zhang [45] also combined the DOI theory to study the dissemination process of generative AI in education, especially how educators can integrate generative AI into teaching.

3.1.3. Cognitive and regulatory theory

A key issue in the AI integration process is how to regulate students' cognitive load and emotional state. Olugbade *et al.* [49] evaluated the regulatory effect of AI chatbots on cognitive burden based on the cognitive load theory. The results showed that AI helps to simplify the information processing process and improve students' understanding, memory performance, and learning outcomes. Dang *et al.* [43] used the socially shared regulation in learning and combined the three-level analysis method of human-computer collaboration to identify two deliberation modes of students in collaborative learning. They found that AI-supported collaboration helps to improve the adaptability of regulatory strategies and the effectiveness of cooperation.

3.1.4. Sociocultural and constructivist theory

This type of theory emphasizes the cultural and cognitive intermediary role of AI in learning. Alghasab [50] used SCT to propose that AI writing tools can support students' ability construction in conception, vocabulary expansion, and language expression. Ling *et al.* [42] combined constructivism and sociocultural learning theory to carry out a 12-week experimental research and develop a training framework for co-creating rural murals for AIGC assistance. The findings showed that the framework significantly improved the participants' creativity, cultural understanding, and collaboration ability, showing the application potential of AI in cultural identity.

3.1.5. Literacy development theory

Wu and Zhang [45] combined the digital literacy development theory, TAM, and DOI to reveal the significant role of generative AI in improving students' digital literacy and innovation ability, and emphasized the key role of teacher training and ethical norms in technology integration. As AI education research deepens, more and more literature begins to integrate across theories and establish a systematic analytical framework. For example, Wu and Zhang [45] combined the diffusion of innovation theory, TAM, and digital literacy theory to systematically explain the cognitive path and capability development mechanism in AI adoption. Chai *et al.* [46] used SDT and TPB to reveal the multiple motivations of students' learning intentions. Ling *et al.* [42] integrated constructivism and sociocultural learning theory to build a collaborative teaching training program supported by AIGC, showing the effectiveness of theoretical integration at the practical level. In addition, some studies have introduced other complementary frameworks, such as Okada *et al.* [44] applied the UNESCO AI Competencies Framework and the CARE-KNOW-DO pedagogical model to provide transformative insights into AI literacy.

Therefore, these theories not only explain learning motivation, adoption behavior, and cognitive regulation but also guide teaching practice. For example, they can be used to design learning tasks based on SDT/TPB to meet psychological needs and reinforce intentions, to enhance students' willingness to use technology based on TAM/UTAUT, and to conduct contextualized, collaborative, and competency-oriented AI teaching by combining socio-cultural, constructivist, and digital literacy frameworks. Meanwhile, teacher support and instructional design are also important external conditions for promoting students' effective use of AI. As a result, current research has first established a methodical route from motivation to competency development in AI education by integrating several ideas. A more systematic cross-theoretical framework or conceptual model is desperately needed in the future, as current investigations still lack a thorough assessment of the similarities, differences, and complementary mechanisms across various theories.

3.2. How do AI tools support functional positioning in student learning?

With the widespread application of AI technology in education, researchers are gradually focusing on its role in supporting student learning. As shown in Table 5, literature indicates that the application of AI in educational environments mainly focuses on multiple dimensions such as writing tutoring, personalized learning, learning motivation stimulation, and emotional regulation, showing a variety of tool types and support methods.

Table 5. AI tools supporting functional positioning in student learning

AI tool	Representative literature	Support methods
ChatGPT/generative artificial intelligence/AIGC	[42], [41], [45]	Supports writing, question-answering, language correction and learning feedback; Improves adaptable learning, innovative problem solving, and critical thinking; Enhances creativity confidence and promotes cultural identity
AI-driven learning analytic	[43]	Identify group regulation and interaction patterns
AI-powered intelligent tutoring system	[47]	Personalized feedback and recommendations
AI Chatbot	[49], [54]	Improve students' learning outcomes, intrinsic motivation, attitudes and memory performance through personalized learning and cognitive load management.
AI tools	[51], [50], [53]	As a writing mediation tool, it helps students to conceive content, enrich vocabulary and improve the accuracy of language expression, thereby supporting the development of their writing skills. At the same time, emotional intervention should be combined to reduce students' anxiety, increase their willingness to use and enhance psychological empowerment.

3.2.1. Use of generative AI tools for writing and language learning

Generative AI (such as ChatGPT) can provide language suggestions, grammatical correction, text reconstruction, and thought stimulation during the writing process. Studies have shown that such tools not only help improve students' language expression skills, but also promote the growth of their critical thinking skills and creativity [41], [45]. In addition, Ling *et al.* [42] further proposed that AIGC technology can enhance students' cultural identity and creative confidence and become an important resource for cultivating cross-cultural capabilities.

3.2.2. AI-powered intelligent tutoring system and AI-driven learning analytics

AI-driven intelligent tutoring systems and learning analytics technologies provide learners with learning path recommendations and personalized feedback. Ni and Cheung [47] demonstrated how intelligent tutoring systems can identify students' learning behaviors and tailor learning suggestions to effectively improve learning efficiency. Dang *et al.* [43] revealed group adjustment patterns and interaction structures through AI learning analytics, providing an empirical basis for collaborative learning optimization and showing the potential of AI in adjustment support.

3.2.3. AI chatbots improve motivation and emotional support

AI chatbots have shown favorable results in improving students' intrinsic motivation and emotional management. Previous research [49], [54] indicated that chatbots can help students feel more engaged and improve their learning by imitating real conversations, offering personalized help, and managing how much information they have to process.

3.2.4. AI-enabled psychological support and anxiety intervention

In addition to the cognitive level, AI tools are also used for psychological empowerment and emotional regulation. Previous research [51], [53] emphasized that in the process of AI tools intervening in education, emotional support strategies should be combined to reduce students' anxiety, increase their willingness to use AI and enhance their sense of self-efficacy. This kind of study has encouraged the shift in the function of AI tools from cognitive intermediary to psychological enabler. In summary, the utilization of AI in education has gone beyond mere assistance in teaching tasks to encompass the holistic development of students' emotions, intellect, and motivation. Future study should investigate the function of AI in cross-cultural adaptation to facilitate a profound integration of technology and educational objectives, considering teacher support and ethical implications.

3.3. What are the beneficial impacts of AI integration on student learning, and what challenges does it encounter?

As shown in Table 6, although AI technology has shown substantial educational potential, relevant research has also revealed the positive effects and potential challenges in its practical application. Integrating AI into education is a prospect full of opportunities, but it also brings significant challenges and requires ethical considerations [64].

Table 6. Beneficial impacts and challenges of AI integration on student learning

No.	Author	Beneficial impacts	Challenges
1	[41]	Personalized learning and support	Loss of academic integrity and the risk of dependency
2	[42]	Enhance access to resources, cultural understanding, and engagement	The gap between theory and evidence
3	[43]	Optimizing collaborative learning regulation recognition	In the absence of strategies, metacognitive interventions fail.
4	[44]	Cultivate AI literacy and emotional responsibility	Structural resource inequality
5	[45]	Improving innovation and digital literacy	Insufficient empirical research limits understanding
6	[46]	Enhance learning willingness, autonomy and sense of social value	The teacher's ability limits the students' development
7	[47]	Promote English learning	Technology anxiety and lack of resources
8	[48]	Stimulate learning attitude and public welfare awareness	Technological misunderstandings and ethical disputes
9	[49]	Reduce cognitive load, improve performance and memory	Data privacy and lack of ethical standards
10	[50]	Supporting writing learning and language development	Long-term benefits of developing writing skills are unclear
11	[51]	Improve learning efficiency and adapt motivation	Various AI anxieties interfere with learning motivation
12	[52]	Improve motivation, engagement and positive cognition	Inclusion and diversity research missing
13	[53]	Enhance sense of connection and maintain intrinsic motivation	Differences in initial motivation affect intervention effectiveness
14	[54]	Improve academic performance and intrinsic motivation	The mechanism of intrinsic motivation needs to be verified
15	[55]	Students have a positive attitude towards AI and their willingness to learn is increasing	There is anxiety about AI learning

3.3.1. Positive effects

AI helps improve students' language ability, learning motivation, digital literacy and social responsibility. AI helps improve learning outcomes, such as improving students' language ability, writing skills and academic performance [41], [47]. AI applications can effectively enhance students' learning engagement, learning motivation and positive attitude towards learning [51], [53]. AI environments support students in developing digital literacy, critical thinking and creativity, and promote their comprehensive ability improvement [45]. AI technology can also be used to promote students' cultural understanding, value education and social responsibility [42], [44].

3.3.2. Potential problems

Although AI has shown many advantages in education, its application still faces multiple challenges, such as dependence, ethical norms, technological anxiety, and teachers' ability to teach learners. If everyone relies too much on AI to generate content, the original innovative thinking and critical analysis ability will be weakened [41]. The application of AI involves issues such as tool abuse and data security, and the ethical and performance standards of AI tools are not yet sound [49]. Insufficient resources, technological anxiety, anxiety caused by AI, or differences in ability reduce the willingness to use AI tools, affecting their learning outcomes [47], [51]. Students' ability to learn AI is limited by the teaching ability of teachers, and there is also a lack of empirical study on how AI promotes the advancement of 21st-century skills [45], [46]. Meanwhile, existing research also draws attention to deeper ethical and equity issues, such as student data privacy and transparency in technology use, as well as the potential for AI to exacerbate the digital divide. Furthermore, significant differences may exist in AI education across different regions and income levels; therefore, future research needs to incorporate cross-regional comparisons to ensure the accessibility and equity of AI applications.

4. DISCUSSION

This study systematically reviews the theoretical basis, support methods, and performance of AI in learner-centered education. Overall, the results indicated that AI has demonstrated a great deal of promise in boosting students' motivation for studying, regulating cognitive load, and achieving personalized learning. As Shi and Xu [65] proposed the function of AI in education is gradually shifting from focusing on material performance to emphasizing psychological empowerment.

In response to the first research question, this study summarized 11 core theoretical frameworks, including SDT, TPB, TAM/UTAUT, cognitive load theory, and sociocultural perspective. The research shows a clear trend of cross-theoretical integration. For example, Chai *et al.* [46] combined SDT with TPB to explain students' behavioral intentions in learning AI. Wu and Zhang [45] integrated TAM, DOI, and digital literacy theory to construct a development path in AI applications. This reflects the shift in AI education research from single models to the construction of system mechanisms. This pattern shows that research on AI schooling is progressively moving away from using a single theoretical model and toward using the complementarity of several theories to explain intricate learning mechanisms. Though they still have limits in exposing long-term learning outcomes and socio-cultural elements, theories that focus on motivation and technology adoption (like SDT and TAM) have a lot to offer in terms of describing learning intents and use habits. This is the exact situation in which socio-cultural viewpoints and cognitive theories may successfully complement these constraints.

Regarding the second research question, AI tools such as ChatGPT, AI chatbots, and learning analysis systems are widely used in scenarios such as writing, language learning, personalized feedback, and motivational support [41], [42]. AI can not only improve expression and creativity [45] but also help to establish cultural identity [42]. However, these positive effects do not occur automatically, but are highly dependent on instructional design and emotional support strategies. The benefits of AI tools themselves are not automatic, and they need to be combined with emotional intervention to reduce students' anxiety, increase willingness to use, and enhance psychological empowerment [53], which also shows the importance of emotional support strategies.

Regarding the third research question, AI has achieved remarkable results in improving students' language skills and learning motivation [47], [52], but it has also caused problems such as dependence, data privacy, ethical anxiety and technological anxiety [41], [51]. Especially in the case of insufficient support from teachers or lack of emotional regulation [46], the educational value of AI integration may be limited. Furthermore, although AI has shown a short-term advantage in writing support, the long-term effectiveness of AI in developing writing skills has been unclear for a long time [50].

Therefore, AI in education is more than just a means of disseminating knowledge; it is a sophisticated system that incorporates regulation, feedback, and tailored instruction [66]. A framework for theoretical integration and practical analysis is developed in this study. Future studies might concentrate on student psychological safety, teacher assistance, and technology fairness while extending to various educational levels and cultural backgrounds. Future research could employ mixed approaches or longitudinal study designs to empirically examine the mechanisms by which cross-theoretical frameworks function at different stages of learning, thereby more systematically validating their long-term effects on learning motivation and emotion regulation. According to Eden *et al*. [64], by fostering a more dynamic and immersive learning environment, AI has promise for greatly enhancing student engagement and learning results.

Additionally, there are still a number of important gaps in the literature. Longitudinal information about the long-term impacts of AI on learning is still scarce, for instance, and the majority of the research that is now available concentrates on short-term effects rather than revealing the consequences of prolonged AI use on learning motivation, autonomy, and competence development. Lastly, current educational theories are still inadequate in understanding the learning mechanisms of emotion-aware systems and generative AI due to the rapid advancement of AI technologies. Future research needs to advance more contextual or hybrid theoretical frameworks to adapt to the new learning characteristics of the AI era.

5. CONCLUSION

This study systematically categorizes the applications, supporting technologies, and integration theories of AI in student-centered learning. AI now plays a significant role in assisting students' emotional control and motivation for studying, going beyond basic educational technology interventions. If the right teaching skills and instructional design are available, intelligent tutoring systems and generative AI show great promise for improving language learning, cognition, and creativity.

Despite its accomplishments, this study still has many drawbacks. First of all, the results may not be as broadly applicable as they could be because this study is restricted to English-language literature that is indexed in the WoS and Scopus databases, and there are only a small number of papers included (n=15). Second, while this study is a SLR, it does not look at the long-term effects of integrating AI into education and instead depends on secondary data. Thus, empirical research—particularly mixed-methods or longitudinal research—is required to further confirm the efficacy of cross-theoretical frameworks in various learning environments. However, issues such as uneven resource allocation, ethical ambiguity, and technological anxiety remind educators that the use of AI is inextricably linked to ethical practice. Future research and applications must be learner-centered and committed to building a sustainable ecosystem that integrates AI with educational responsibility.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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