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Gamification Meets Artificial Intelligence in Mathematics Education: A Review of Personalized Learning and Student Engagement

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ABSTRACT

This study presents a Systematic Literature Review (SLR) examining the integration of gamification and Artificial Intelligence (AI) in mathematics education, with a particular focus on personalized learning and student engagement. The review synthesizes scholarly articles published over the last ten years, sourced from reputable databases including Scopus, DOAJ, and Google Scholar. A rigorous selection process was employed to identify relevant empirical and theoretical studies that explore the intersection of AI-driven technologies, gamified learning environments, and key psychological constructs. The findings reveal that the convergence of gamification and AI significantly enhances students' learning experiences by promoting adaptive, personalized instruction and increasing engagement through interactive and motivational elements. Moreover, the results highlight the central role of psychological variables especially motivation and self-efficacy in mediating the relationship between AI-supported gamified environments and learning outcomes. From an interpretative standpoint, the evidence underscores a socio-cognitive mechanism in which psychological readiness constitutes the principal pathway through which AI exerts its influence on learning processes. Despite these promising outcomes, the review also identifies several limitations within the current body of literature, including a predominance of correlational research designs and an underrepresentation of contextual and longitudinal perspectives. Therefore, future research is recommended to adopt more comprehensive and methodologically robust approaches to better understand the long-term and causal impacts of AI-integrated gamification in mathematics education.

Keywords: Artificial Intelligence; Gamification; Student Engagement; Personalized Learning.

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1. INTRODUCTION

The rapid transformation of education in the digital era necessitates strategic innovations in mathematics instruction, a subject often perceived as complex, abstract, and less appealing to many students. In the Indonesian context, low levels of mathematical literacy remain a persistent challenge, as reflected in suboptimal performance in international assessments (Rachmawati & Rofiq, 2023). Furthermore, the inherently abstract and procedural nature of mathematics contributes to students' limited engagement during the learning process (Rachma et al., 2024). These conditions underscore the urgent need for technology-enhanced learning approaches that are not only interactive and adaptive but also capable of fostering meaningful learning experiences.

This issue is further exacerbated by the low level of student engagement, which has a direct impact on students' motivation and academic achievement. The predominance of teacher-centered instructional models often results in passive learning behaviors and reduced interest in mathematical content (Rijal & Maharani, 2024). In this context, gamification has emerged as a promising pedagogical approach that effectively enhances both motivation and engagement in mathematics learning environments (Putri & Muhtadi, 2023). Moreover, gamification-based learning media contribute to more interactive, engaging, and enjoyable learning experiences, thereby encouraging active student participation.

With the advancement of educational technology, gamification has increasingly been implemented as an innovative approach in modern mathematics education. The integration of game elements such as points, levels, and challenges has been shown to significantly improve students' learning motivation, with reported increases exceeding 20% compared to conventional instructional methods (Anggi, 2025). Additionally, the use of augmented reality within gamified learning environments provides more immersive and contextualized experiences, leading to improvements in conceptual understanding by approximately 25–30% in experimental studies (Sani et al., 2025). Evidence from systematic literature reviews further indicates that nearly 80% of empirical studies report significant improvements in student engagement through gamified mathematics learning (Prasetyo & Meiliasari, 2025). The growing body of literature also reveals a consistent increase in publications on gamification in mathematics education over the past five years, with an annual growth rate exceeding 15% (Karnilah et al., 2024). In addition, gamification-based learning media have been shown to generate positive student responses, with satisfaction and engagement levels surpassing 85% across various educational levels (Khauli et al., 2021). These findings highlight that gamification functions not merely as an instructional tool but as an effective pedagogical strategy to enhance interaction and learning experiences.

On the other hand, the emergence of Artificial Intelligence (AI) in education offers substantial opportunities to develop adaptive learning systems through personalized learning approaches. AI technologies enable the customization of instructional content, difficulty levels, and delivery strategies based on individual student needs and characteristics. Furthermore, AI can provide real-time feedback, allowing students to promptly identify and correct their misunderstandings, thereby improving conceptual comprehension in mathematics (Chen et al., 2020). AI also facilitates continuous analysis of students' learning data to detect learning patterns, monitor progress, and identify potential difficulties (Zawacki-Richter et al., 2019). The integration of AI into educational settings has been shown to significantly enhance the quality of technology-based learning by delivering more personalized, interactive, and responsive learning experiences (G.-J. Hwang et al., 2020). Thus, AI represents a strategic component in advancing more effective and student-centered mathematics education.

Despite the substantial potential of both gamification and Artificial Intelligence in improving mathematics learning particularly in terms of student engagement and personalized learning the integration of these two approaches remains underexplored and fragmented across the existing literature. There is a lack of comprehensive synthesis that systematically examines how these approaches interact and contribute to learning outcomes in mathematics education. Therefore, this study aims to conduct a Systematic Literature Review (SLR) to identify research trends, analyze the roles, and synthesize empirical findings related to the integration of gamification and Artificial Intelligence in mathematics education. Additionally, this study seeks to provide conceptual insights and future research directions for the development of more innovative, adaptive, and student-centered technology-enhanced learning environments.

2. RESEARCH METHODS

This study adopts a qualitative research design employing a Systematic Literature Review (SLR) approach to systematically examine the integration of gamification and Artificial Intelligence (AI) in mathematics education. In line with the research objective, this study aims to identify research trends, analyze the roles and interactions, and synthesize empirical findings related to how gamification and AI collectively contribute to student engagement and personalized learning. Furthermore, this review seeks to address the existing fragmentation in the literature by providing a comprehensive and structured synthesis, as well as generating conceptual insights and future research directions for the development of innovative, adaptive, and student-centered technology-enhanced learning environments.

The literature search was conducted using a systematic and transparent strategy across major academic databases, including Scopus, DOAJ, and Google Scholar, to ensure broad and high-quality coverage of relevant studies. The search process employed combinations of keywords and Boolean operators such as "gamification AND artificial intelligence AND mathematics education," "AI-driven learning AND student engagement," and "personalized learning AND gamification." To capture contemporary developments and align with the study's objective of identifying recent trends, the search was limited to publications from the last ten years (2016–2025). Only peer-reviewed journal articles and conference proceedings published in English were included to ensure academic rigor and relevance.

To ensure alignment with the research objectives, explicit inclusion and exclusion criteria were established. The inclusion criteria comprised: (1) studies investigating the integration or combined application of gamification and AI in mathematics education; (2) research examining student engagement and/or personalized learning as key outcomes; (3) empirical studies, systematic reviews, or conference papers providing substantive findings; and (4) publications within the defined time frame (2016–2025). Conversely, the exclusion criteria included: (1) studies focusing solely on gamification or AI without addressing their interaction or relevance to the study focus; (2) research outside the domain of mathematics education; (3) non-peer-reviewed publications such as opinion pieces or editorials; and (4) studies lacking methodological clarity or empirical contribution.

The study selection process followed a structured procedure adapted from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and replicability. Initially, a total of 75 articles were retrieved from several academic databases through keyword-based searches related to gamification, artificial intelligence, and mathematics learning. Initially, all retrieved records were screened based on titles and abstracts to identify studies relevant to the integration of gamification and AI. During the screening stage, 21 duplicate articles were removed, while 24 articles were excluded because they did not specifically discuss mathematics learning or did not address the integration between gamification and AI. Subsequently, full-text screening was conducted to ensure that the selected studies explicitly addressed the interaction, contribution, or combined impact of these approaches on student engagement and personalized learning. At the eligibility stage, 12 additional articles were excluded because the studies lacked sufficient methodological information or did not report relevant learning outcomes. As a result, a final total of 18 articles met all inclusion criteria and were selected for analysis. Duplicate articles were removed during the initial phase. Data extraction was carried out using a standardized coding scheme that included key variables such as authorship, publication year, research design, type of technology integration (gamification, AI, or both), targeted learning outcomes, and major findings. The extracted data were then analyzed using a thematic synthesis approach to identify recurring patterns, research trends, interaction models, and gaps in the literature, thereby supporting a comprehensive understanding of how gamification and AI jointly influence mathematics learning, as shown in **Figure 1**.

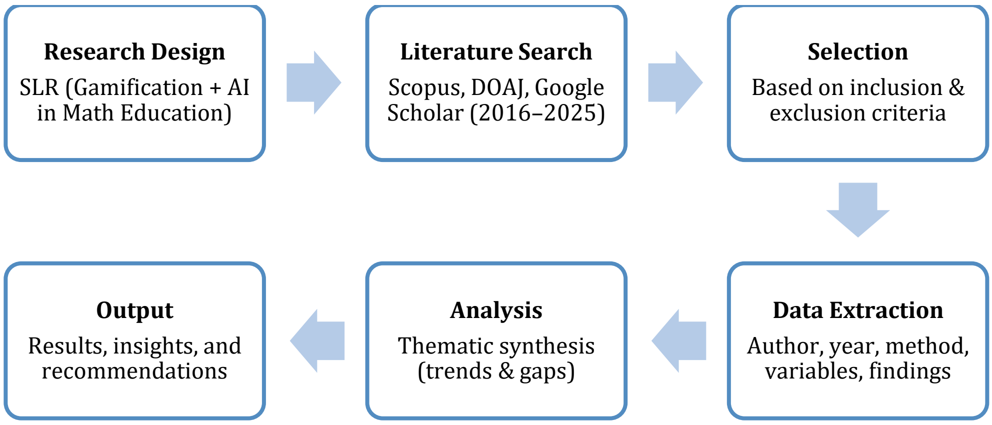

Figure 1. *Research Methodology Framework for the Systematic Literature Review*

3. RESULTS AND DISCUSSION

The findings of this systematic literature review (SLR) reveal a coherent and evolving body of knowledge concerning the integration of Artificial Intelligence (AI) in education, particularly in relation to technological innovation, psychological determinants, learning outcomes, and methodological approaches. Through a rigorous synthesis of the selected studies, it becomes evident that AI is not only transforming instructional practices but also reshaping the underlying mechanisms of learning by interacting with key psychological variables such as motivation and self-efficacy. Furthermore, the literature demonstrates a growing emphasis on adaptive learning systems, human–AI interaction, and advanced analytical techniques in examining educational effectiveness. To provide a structured overview of these research trends, the main findings are categorized based on their thematic focus, associated authors, and key research variables, as presented in **Table 1**.

Table 1. *Thematic Classification of AI in Education Research Based on Focus, Authors, and Key Insights*

No	Research Focus / Domain	Authors	Key Insights / Research Variables
1	AI Integration and Technological Innovation in Education	Ng et al. (2021); Zawacki-Richter et al. (2019); Holmes et al. (2019); Kasneci et al. (2023)	AI literacy, generative AI, adaptive learning systems, digital transformation, personalized learning, technology adoption
2	Psychological Variables in AI-Supported Learning	Ryan & Deci (2020); Scherer et al. (2019); Schunk & DiBenedetto (2020); Tondeur (2017); Alamri (2022); Honicke & Broadbent (2016)	Motivation, anxiety, self-efficacy, engagement, persistence, resilience, psychological readiness
3	Learning Outcomes and Educational Effectiveness	Hwang et al. (2020); Zawacki-Richter (2019); Hattie & Timperley (2017)	Academic performance, student satisfaction, engagement, learning

No	Research Focus / Domain	Authors	Key Insights / Research Variables
			achievement, feedback effectiveness
4	Human–AI Interaction and Cognitive Processes	Luckin et al. (2016); Holmes et al. (2019); Kasneci et al. (2023)	Human–AI interaction, cognitive engagement, learner autonomy, higher-order thinking, knowledge construction
5	Methodological Approaches in AI Education Research	Hair et al. (2019); Sarstedt et al. (2020); Ringle et al. (2020)	SEM, PLS-SEM, structural modeling, mediating variables, causal relationships, predictive analysis

To further elucidate the intellectual structure and thematic relationships within the reviewed literature, a bibliometric analysis was conducted using VOSviewer to map the co-occurrence of keywords. This visualization provides a comprehensive overview of how key concepts are interconnected and clustered, thereby reflecting dominant research themes and emerging trends in the field of Artificial Intelligence in education. The resulting network, as illustrated in **Figure 2,** highlights the distribution of major topics such as technological implementation, psychological variables, and learning outcomes, offering deeper insight into the evolving landscape of AI-driven educational research.

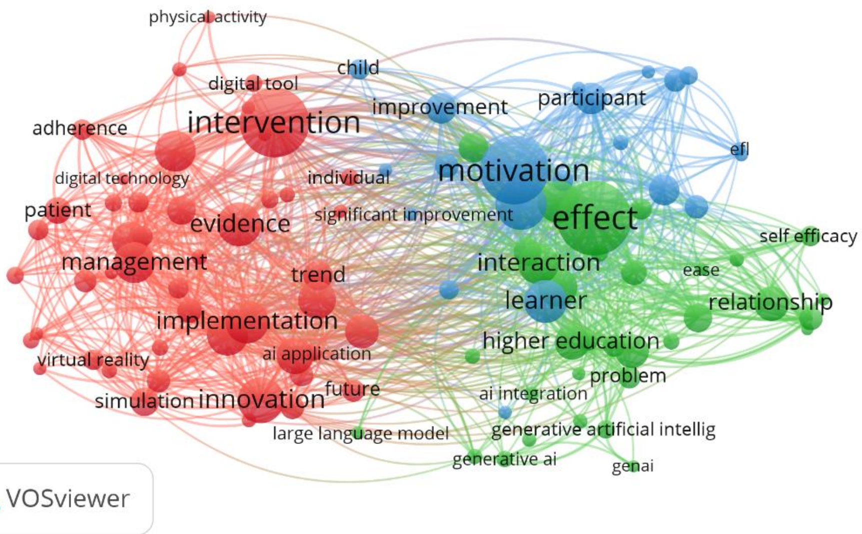

Figure 2. Co-occurrence Network Visualization of Research using VOSviewer

Red Cluster: Intervention, Health, and Technology Implementation

The red cluster is dominated by keywords such as intervention, health, care, management, implementation, evidence, patient, digital technology, accessibility, privacy, simulation, medical education, and innovation, indicating a high density of interconnections within the domain of digital health. Conceptually, this cluster represents the field of technology-based interventions in healthcare and medical education, encompassing the use of digital technologies to enhance healthcare services (digital health interventions), the implementation of Artificial Intelligence (AI)-based systems and simulations in medical education, and the application of evidence-based practices. The interpretation of the keyword relationships suggests that digital transformation in healthcare has shifted from mere innovation toward practical implementation and effectiveness evaluation. Furthermore, research focus extends beyond technological development to include critical issues such as accessibility, data privacy, and the quality of patient care. The strong linkage with medical education indicates that technologies, including AI and simulation tools, play a significant role in improving healthcare professionals' competencies. Therefore, this cluster can be interpreted as the foundational basis for applied AI in real-world contexts, particularly within healthcare and professional education sectors.

Blue Cluster: Motivation, Performance, and Experimental Design

The blue cluster includes keywords such as motivation, performance, participant, control group, questionnaire, language learning, anxiety, and improvement, reflecting a close relationship between psychological variables and experimental approaches. This cluster represents empirical research grounded in experimental design, aiming to measure the impact of technological interventions on individuals' psychological aspects and performance, particularly in learning contexts. The primary focus includes learning motivation, academic performance, and quantitative evaluation methods such as control group designs. The network structure indicates that AI-based learning technologies, including gamification, are predominantly tested using systematic experimental approaches. Variables such as motivation and anxiety function as critical mediators influencing the success of interventions. Meanwhile, the prevalence of questionnaire-based methods suggests that most studies rely heavily on self-reported data, which may introduce subjectivity bias. Consequently, this cluster highlights that the effectiveness of AI implementation in education is not solely determined by technological sophistication but is also significantly influenced by users' psychological factors.

Green Cluster: Learning Outcomes, Generative AI, and Higher Education

The green cluster is characterized by keywords such as effect, learner, interaction, satisfaction, self-efficacy, generative AI, higher education, mathematics, AI integration, and relationship SEM/PLS, demonstrating strong connections between AI technologies and learning outcomes. This cluster represents the integration of Artificial Intelligence, particularly Generative AI, within higher education and its impact on various learning outcomes. It encompasses aspects such as learning effectiveness, human–AI interaction, and the application of advanced analytical models, including Structural Equation Modeling (SEM) and Partial Least Squares (PLS), to examine relationships among variables. The interpretation of this cluster reveals a paradigm shift from viewing technology as a supportive tool to recognizing it as an active partner in the learning process, especially with the emergence of generative AI and large language models. The emphasis on variables such as self-efficacy and satisfaction underscores the importance of user experience in determining the success of technology integration. Additionally, the use of advanced statistical techniques such as SEM/PLS indicates a growing trend toward more complex and integrative analytical approaches. Thus, this cluster reflects the current state-of-the-art research direction in AI-driven education, particularly in relation to personalized learning and optimization of educational outcomes.

The integration of these three clusters forms a systematic conceptual framework based on the Input–Process–Output (IPO) model. The red cluster serves as the input, representing technology- and AI-based interventions in various contexts, particularly healthcare and education. The blue cluster functions as the process, reflecting psychological mechanisms such as motivation, anxiety, and individual participation in response to these interventions. Meanwhile, the green cluster represents the output, capturing the impact of these interventions on learning outcomes, including effectiveness, satisfaction, and academic performance. This synthesis demonstrates that the success of AI implementation cannot be understood in isolation but must be analyzed holistically through the interaction between technological interventions, psychological processes, and resulting outcomes. The model further emphasizes the importance of a multidisciplinary approach in AI research, integrating technological, psychological, and educational perspectives simultaneously.

1.1 Cluster Patterns and Research Trends in AI in Education

The distribution of keywords identified through bibliometric mapping reveals a strong thematic concentration on technology integration, psychological variables, and learning outcomes within the context of Artificial Intelligence (AI) in education. This pattern indicates that the research landscape has evolved from fragmented inquiries into a more structured and interconnected knowledge domain. Empirical evidence suggests that AI literacy, motivation, and self-efficacy are critical constructs influencing students' readiness to adopt intelligent technologies (Ng et al., 2021). Furthermore, psychological dimensions such as growth mindset and self-efficacy play a pivotal role in enhancing motivation in technology-supported learning environments (Zawacki-Richter et al., 2019a). In addition, motivation has been identified not only as an independent predictor but also as a mediating variable linking engagement and academic performance in AI-supported learning contexts (G.-J. Hwang et al., 2020). Therefore, the clustering of keywords reflects a convergence of technological, psychological, and pedagogical dimensions in contemporary AI research in education.

From an evolutionary perspective, research trends demonstrate a paradigm shift from conventional digital interventions toward the integration of generative AI as an active agent in the learning process. Adaptive AI-based learning systems have been shown to enhance students' motivation and self-efficacy through personalized learning pathways (Holmes et al., 2019). Moreover, real-time feedback generated by AI technologies contributes significantly to improving cognitive engagement and learner autonomy (Luckin et al., 2016). At the same time, the adoption of AI tools, including generative AI, has been associated with improved academic achievement, particularly when mediated by intrinsic motivation (Kasneci et al., 2023). Hence, this evolution not only reflects technological advancement but also signifies an epistemological transformation in perceiving AI as a cognitive partner in education.

The identified keyword clusters indicate a significant conceptual shift in AI research in education from a technology-centered perspective toward a more integrative socio-cognitive approach. The strong linkage between psychological variables, such as motivation and self-efficacy, and technological elements suggests that AI effectiveness is increasingly understood as dependent on internal learner characteristics, aligning with theories of self-regulated and personalized learning. The emergence of generative AI further reflects a transition from passive tool usage to active human–AI collaboration, positioning AI as a cognitive partner in facilitating higher-order thinking. However, despite this advancement, the literature tends to overemphasize individual psychological factors while underrepresenting contextual and institutional dimensions, including ethical and policy considerations. Methodologically, the dominance of SEM/PLS approaches demonstrates analytical rigor but also highlights limitations in causal inference due to the lack of experimental and longitudinal studies. Overall, the clustering patterns reflect both the maturation of the field and the need for more comprehensive and methodologically diverse research.

1.2 The Role of Psychological Variables in AI Effectiveness

In the implementation of AI in education, psychological variables such as motivation, anxiety, and engagement play a crucial role in determining learning effectiveness. Intrinsic motivation has been consistently found to have a direct positive effect on student engagement and academic performance in AI-supported learning environments (Ryan & Deci, 2020). Additionally, recent empirical findings suggest that the relationship between motivation and engagement is mediated by self-efficacy, which functions as an internal psychological mechanism that strengthens the learning process (Scherer et al., 2019). Studies also demonstrate that AI-enhanced learning environments significantly influence students' motivation when supported by high levels of perceived competence and self-efficacy (Schunk & DiBenedetto, 2020). Thus, the effectiveness of AI integration is not solely dependent on technological sophistication but also on the psychological readiness of learners.

Self-efficacy emerges as a key construct that bridges the relationship between technology use and learning outcomes. Higher levels of self-efficacy significantly contribute to students' readiness and confidence in utilizing AI technologies effectively (Tondeur, 2017). Moreover, self-efficacy influences students' persistence and resilience in engaging with complex digital learning environments (Alamri, 2022). Recent studies further confirm that self-efficacy acts as a mediating variable that strengthens the relationship between digital learning environments and academic achievement (Honicke & Broadbent, 2016). Therefore, self-efficacy can be positioned as a strategic variable in explaining the success of AI integration in education.

From an interpretative standpoint, the existing evidence underscores a socio-cognitive mechanism in which psychological readiness constitutes the principal pathway through which AI exerts its influence on learning processes. In particular, self-efficacy functions as a pivotal internal regulator that shapes learners' confidence, persistence, and adaptability in navigating complex AI-supported environments, thereby positioning AI not merely as an instructional medium but as a catalytic agent whose effectiveness is contingent upon learners' psychological states. The dynamic interplay among motivation, anxiety, and self-efficacy further illustrates that positive psychological conditions facilitate engagement and performance, whereas negative factors, such as anxiety, may impede the optimal utilization of AI technologies. Nevertheless, a critical appraisal of the literature reveals several limitations, including an overemphasis on positive psychological constructs at the expense of negative variables, a reliance on self-reported data prone to bias, and the dominance of cross-sectional and correlational designs that constrain causal inference. Collectively, these issues highlight the need for more balanced, methodologically rigorous, and longitudinal investigations to advance a more comprehensive understanding of psychological dynamics in AI-supported learning environments.

1.3 The Impact of AI Integration on Learning Outcomes

The integration of Artificial Intelligence in education has demonstrated a significant impact on both learning performance and student satisfaction. AI-based adaptive learning systems enhance academic performance by delivering personalized learning experiences tailored to individual needs (Zawacki-Richter, 2019). Additionally, real-time feedback provided by AI systems contributes to increased student satisfaction and engagement in the learning process (Hattie & Timperley, 2017). Furthermore, the interaction between AI usage, motivation, and self-efficacy has been shown to positively influence students' academic achievement (Hwang et al., 2020). Thus, AI serves as a transformative agent in improving the quality of educational outcomes.

To analyze the complex relationships among variables in AI-supported learning environments, structural modeling approaches such as Structural Equation Modeling (SEM) and Partial Least Squares (PLS) have become dominant methodologies. SEM has proven effective in identifying causal relationships among constructs such as motivation, self-efficacy, and academic performance (Hair et al., 2019). In addition, PLS-SEM is widely used to examine predictive relationships in technology-enhanced learning contexts due to its robustness in handling complex models and small sample sizes (Sarstedt et al., 2020). Empirical studies also confirm that SEM/PLS approaches are capable of explaining the mediating role of self-efficacy in the relationship between AI usage and learning outcomes (Ringle et al., 2020). Therefore, SEM and PLS provide critical methodological contributions to understanding the dynamics of AI integration in education.

From an interpretative perspective, the evidence indicates that Artificial Intelligence (AI) functions as a transformative pedagogical agent, shifting learning from a standardized paradigm toward a more personalized and adaptive model, wherein technological capabilities are translated into meaningful learning outcomes through learners' psychological engagement and self-regulation. In this context, AI extends beyond enhancing instructional delivery to actively shaping how learners interact with content and construct knowledge. Nevertheless, a critical appraisal of the literature reveals notable limitations, including a tendency to overgeneralize AI effectiveness without adequately considering contextual variability such as learning environments, access to technology, and instructional design differences. Furthermore, the predominance of cross-sectional designs and self-reported data raises concerns regarding the robustness and generalizability of findings, thereby underscoring the need for more rigorous experimental and longitudinal research to establish causal relationships and long-term impacts of AI integration in education. The following is a keyword mind map based on research trends (2016–2025), as shown in **Figure 3**.

Figure 3. Mind Map Keywords Based on Research Evolution (2016–2025)

The synthesis of the identified keywords across the 2016–2025 period reflects a clear and progressive conceptual evolution in AI research within education, moving from a technology-centered paradigm toward a holistic, socio-cognitive, and methodologically sophisticated framework. In the early phase (2016–2017), AI was predominantly positioned as an instructional support tool, emphasizing digital learning environments, intelligent tutoring systems, and real-time feedback to enhance basic cognitive engagement and learner autonomy. This focus gradually expanded in the 2018–2019 period, where personalization and psychological constructs such as motivation, self-efficacy, and growth mindset emerged as critical factors, indicating a shift toward understanding learning as an interaction between technology and internal learner characteristics. The subsequent phase (2020–2021) marked a deeper integration of these elements, highlighting the mediating role of psychological variables particularly self-efficacy in linking AI usage to learning outcomes such as academic performance, engagement, and satisfaction. Entering the 2022–2023 phase, the emergence of generative AI signified a paradigmatic transition, wherein AI is no longer perceived merely as a tool but as an active learning partner facilitating higher-order cognitive processes, including critical thinking and problem-solving. Finally, the most recent phase (2024–2025) demonstrates a maturation of the field, characterized by the adoption of comprehensive frameworks such as socio-cognitive learning models, the incorporation of ethical considerations (e.g., algorithmic bias and academic integrity), and the use of advanced methodological approaches such as SEM and PLS-SEM to analyze complex relationships. Collectively, these developments indicate that AI in education has evolved into an integrated ecosystem in which technological innovation, psychological readiness, pedagogical processes, and methodological rigor are deeply interconnected.

2. CONCLUSIONS AND SUGGESTIONS

In conclusion, this systematic literature review demonstrates that the integration of Artificial Intelligence (AI) in education has evolved into a multidimensional and socio-cognitively grounded domain, wherein learning effectiveness is shaped not only by technological sophistication but also by learners' psychological readiness, particularly motivation and self-efficacy, as well as their interaction with adaptive and personalized learning environments. The evidence consistently positions AI as a transformative pedagogical agent capable of enhancing learning outcomes through dynamic human–AI collaboration; however, the literature remains limited by an overemphasis on individual psychological variables, insufficient consideration of contextual and ethical dimensions, and a predominance of correlational research designs. Therefore, it is recommended that future studies adopt more comprehensive and methodologically rigorous approaches, including longitudinal and experimental designs, while integrating psychological, technological, and socio-institutional factors within unified frameworks. Additionally, greater scholarly attention should be directed toward emerging issues such as AI ethics, algorithmic bias, and the potential negative psychological impacts of AI usage to ensure a more balanced and sustainable development of AI in educational practice.

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