SHAPING SELF-REGULATED AND METACOGNITIVE LEARNING THROUGH ARTIFICIAL INTELLIGENCE AND LEARNING ANALYTICS

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Abstract: *Artificial intelligence (AI) and learning analytics are increasingly embedded in educational systems, yet their implications for self-regulated learning (SRL) and metacognitive development remain only partially understood. This study conducts a systematic literature review of 34 empirical and review articles investigating AI-driven learning analytics in formal education settings, focusing on their impact on SRL, motivation, and academic performance. Following PRISMA-aligned procedures, the review identifies studies involving AI-based analytics tools, standardized SRL or metacognitive assessments, and empirical designs with pre–post or comparison data. The results indicate that AI-driven systems such as predictive models, adaptive platforms, chatbots, and generative AI can strengthen core SRL processes, increase motivation and engagement, and improve academic outcomes across diverse subjects and educational levels. However, the review also reveals persistent implementation challenges, including infrastructural limitations, teacher preparedness, privacy and ethical issues, and potential over-reliance on AI that may weaken independent strategic thinking. The article concludes that AI-driven learning analytics can meaningfully support SRL when embedded within coherent pedagogical frameworks and supported by institutional policies, and it outlines directions for future research on mechanisms, equity, and long-term effects.*

Keywords*: AI in education, Learning analytics, Self-regulated learning, Metacognition.*

INTRODUCTION

Artificial intelligence (AI) has become a major driver of innovation in education, changing how learning is designed, delivered, and evaluated across disciplines and levels of education. Recent systematic reviews and scoping reviews document the rapid expansion of AI-based learning systems, including intelligent tutoring systems, adaptive platforms, and predictive analytics that aim to personalize learning and support decision-making in complex learning environments (Lin et al., 2023; Wang et al., 2024). This development extends to various domains such as higher education, medical education and special needs education, as well as technology-based learning more generally, reflecting growing expectations that AI will play a structural role in the future educational ecosystem (Gordon et al., 2024).

In parallel, self-regulated learning (SRL) has increasingly been affirmed as a core competency for learners operating in digital and online environments. SRL

describes learners' ability to set goals, select strategies, monitor progress, and reflect on learning outcomes, and it has been identified as a key success factor in e-learning and blended learning (Araka et al., 2020; Deneen, 2025). Various systematic reviews on SRL in the digital era highlight that students increasingly rely on a combination of cognitive, metacognitive, and motivational strategies to manage their learning, yet many still struggle to sustain effective regulation without targeted support (Faza & Lestari, 2025; Xue et al., 2025). These findings position SRL as a natural focus for understanding how AI not only delivers content but also has the potential to shape learners' agency and learning autonomy over time (Araka et al., 2020; Faza & Lestari, 2025).

Within this broader landscape, AI technologies are increasingly used to scaffold specific SRL processes, rather than merely serving as tools for presenting material. Qualitative studies and systematic reviews in higher education show that AI-enriched learning environments can encourage learners to plan learning activities, monitor performance, and adjust strategies based on adaptive feedback and analytics-based insights (Lan & Zhou, 2025). Learning analytics dashboards and recommender systems help students track progress, manage time, and identify risk patterns, thereby supporting the behavioral and monitoring dimensions of SRL in online learning and MOOC contexts (Xue et al., 2025). At the same time, research on educational chatbots shows that conversational agents can help identify learning resources and clarify understanding in real time in independent learning scenarios, thus extending support for SRL into everyday interactions with learning platforms (Guan et al., 2024; Mohebbi, 2024).

In more recent developments, generative AI and conversational AI are positioned as cognitive partners that can influence learners' metacognitive and reflective practices. Systematic reviews report that generative AI can provide personalized explanations, hints, and reflective prompts that encourage students to articulate their reasoning, compare different solutions, and revise their understanding, with early evidence indicating positive effects on self-regulated learning and critical thinking skills (Sardi et al., 2025; Goyal, 2025). Studies on AI-assisted autonomous learning in vocational and higher education also indicate that AI-based systems can support goal setting and strategy selection by providing structured learning pathways and personalized recommendations (Juan & Nagappan, 2025). In addition, studies on AI-mediated metacognitive and emotional support affirm that AI can be integrated into broader frameworks targeting the psychological and reflective dimensions of learning, not merely cognitive performance (Chardonnens, 2025; Deckker & Sumanasekara, 2025).

Despite these promising developments, the literature also highlights various risks and unresolved tensions regarding how AI shapes SRL. Reviews of AI-assisted learning environments warn that immature structures or excessive reliance on AI can foster dependence on automated suggestions, reduce opportunities for "productive struggle," and encourage shallow engagement, especially when AI is used primarily as an instant answer provider (Sardi et al., 2025). Ethical and equity issues further complicate the situation, as studies on AI in online learning and language learning highlight challenges related to data privacy, algorithmic bias, and unequal access to AI-rich infrastructure, which may affect learners' capacity to exercise self-regulation differently (Mohebbi, 2024). At the same time, analyses of

AI implementation in medical education and special needs education show that highly domain-specific implementations raise their own questions regarding transparency, trust, and the appropriate level of automation in high-stakes learning contexts (Hussein et al., 2025).

A chronological review shows that research on AI and SRL has grown rapidly since 2020, yet it remains fragmented across domains, technologies, and methodological traditions. Some reviews focus on intelligent tutoring systems and sustainable AI-based instruction, while others highlight AI in medical curricula, special education, or psychological and emotional education, which are often discussed separately (Deckker & Sumanasekara, 2025). Additional syntheses examine how generative AI transforms assessment practices or how AI tools support learner autonomy in language education, yet these contributions rarely systematically connect SRL constructs with learning outcomes (Xia et al., 2024). As a result, integrated evidence remains limited that simultaneously maps the types of AI tools, the targeted SRL subprocesses, their impact on motivation and academic performance, and the technical, pedagogical, and ethical challenges that mediate these effects (Aguado-García et al., 2025).

In this context, this study conducts a systematic literature review to synthesize contemporary evidence on how artificial intelligence (AI) and learning analytics influence self-regulated learning (SRL) across various educational contexts. This review aims to (1) map how various AI tools and analytic approaches are applied to support self-regulated learning (SRL) and related outcomes such as motivation and academic achievement, (2) evaluate the magnitude and consistency of the reported effects on self-regulation and learning performance, and
(3) identify implementation mechanisms and conditions that help explain the heterogeneity of findings and emerging challenges.

METHODS

This study employs a systematic literature review design to provide a comprehensive overview of how learning analytics driven by artificial intelligence (AI) influence students' independent learning ability and metacognitive skills in formal education. The review process involved formulating the research problem, establishing clear inclusion and exclusion criteria, and arranging search and screening procedures in accordance with PRISMA guidelines to ensure rigor and transparency.

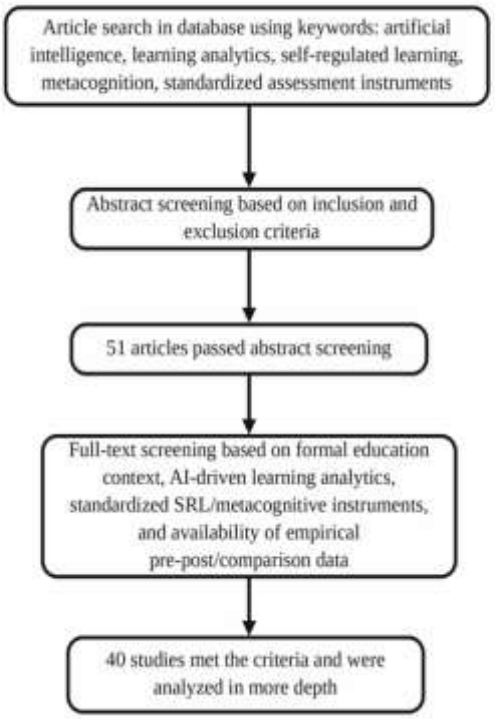


Figure 1. Data Selection and Identification

The dataset in this study consists of empirical articles and review articles drawn from a scholarly database using a structured search strategy that combined keywords related to artificial intelligence and learning analytics, self-regulated learning and metacognition, and standardized assessment instruments. This search yielded 500 articles that matched the general keyword and topic criteria, which were then taken to the systematic screening stage.

Study selection was carried out in two stages. In the abstract screening stage, articles were retained if their summaries indicated that: (1) the study population consisted of students in formal education settings (K–12, higher education, or vocational), (2) the study involved an AI-driven learning analytics intervention that analyzed learning data and provided feedback or recommendations, (3) the outcomes included self-regulated learning or metacognitive skills measured with standardized instruments, and (4) empirical results were reported. This stage reduced the corpus from 500 to 51 articles eligible for full-text review.

In the full-text screening stage, the same core criteria were applied in greater depth. Articles were included if they: (1) provided adequate detail about the formal education context and participant characteristics, (2) implemented a learning analytics system with an explicit artificial intelligence or machine learning component, rather than merely descriptive statistics, (3) used at least one standardized SRL or metacognitive instrument, although it could be supplemented by researcher-developed scales, and (4) reported pre–post data and/or comparison group results that allowed evaluation of the intervention's impact. Studies that did not meet these requirements, were purely theoretical, or did not present empirical

data were excluded from the analysis. This process yielded 40 studies judged to meet all criteria and included in the final synthesis.

For each of the 40 studies, data were extracted using a structured template. This review documented the characteristics of the AI-driven learning analytics interventions (system type, main features, data sources, and platforms), the standardized SRL or metacognitive instruments and their administration procedures, findings on the impact on specific SRL skills, the research design and participant context, and the mechanisms proposed to explain how analytics systems influence learners' self-regulation. Overall, this set of studies serves as the empirical basis for answering how AI-driven learning analytics are implemented, what impacts they produce on SRL and metacognition, and under what conditions these systems are most effective in formal education settings.

RESULTS AND DISCUSSION

Based on the systematic review process described in the Methods section, the final corpus consisted of 34 empirical and review studies on AI-driven learning analytics and self-regulated learning at the primary, secondary, and higher education levels. The main characteristics of these studies are summarized in Table 1, which includes the author name and year, type of study, education level, population, and methodological approach used.

Table 1. Research Findings

AUTHORS & YEAR	STUDY TYPE	EDUCATION LEVEL	POPULATION	METHOD
Sulaiman Abdul Rasid et al., 2025	Primary study	Higher education	131 university students	Quantitative (PLS-SEM)
Amanullah Amanullah et al., 2025	Systematic literature synthesis	Secondary education	Literature-based	Theory-based synthesis
Lazaro Kumala Dewi et al., 2025	Primary study	Higher education	University students	Descriptive quantitative
Eka Budhi Santosa et al., 2020	Primary study	Higher education	188 university students	Data mining (k-means)
B. P. Gautama et al., 2024	Primary study	Higher education	Student dataset (82% male, 27% female)	Rasch model analysis
Shindy Arti et al., 2025	Primary study	Higher education	675 data points	CRISP-DM method
Nirmala Ardana et al., 2025	Primary study	Higher education	72 respondents	Survey with regression
Satunggale Kurniawan et al., 2025	Research R&D	Secondary education	40 students (trial)	Borg & Gall model
Enry Johan Jaohari et al., 2025	Primary study	Higher education	University students & alumni	Descriptive qualitative

Asyhari A Usman et al., 2025	Primary study	Secondary education	60 students	Quasi-experimental
Selviana Ronsumbre et al., 2023	Primary study	Higher education	University students	Mixed methods
Miftakhuddin et al., 2025	Primary study	Higher education	University students	Mixed methods
Christine Permatasari et al., 2021	Primary study	Secondary education	4 students	Descriptive qualitative
Liina Parn et al., 2025	Primary study	Higher education	135 respondents	SEM with SmartPLS
Sumarlin et al., 2025	Primary study	Higher education	100 university students	Machine learning comparison
M. Fadhilah et al., 2025	Systematic literature review	Primary education	Literature-based	PRISMA
Annas Prasetio et al., 2025	Primary study	Secondary education	60 students	Mixed methods
Muhamad Rizki Suryawijaya et al., 2025	Primary study	Higher education	19 university students	Descriptive qualitative
Syamsidar Hs et al., 2024	Primary study	Higher education	50 university students	Quantitative (questionnaire)
Desty Yani et al., 2025	Systematic literature review	Mixed levels	Literature-based	SLR (2019–2024)
Supriadi Supriadi et al., 2025	Primary study	Secondary education	Grade XI students	Quasi-experimental
Sukarman Purba et al., 2025	Primary study	Higher education	University students	Quantitative survey
Ginati Ayuningtyas et al., 2024	Primary study	Higher education	24 participants	Descriptive quantitative
Muttaqin Kholis Ali et al., 2025	Primary study	Secondary education	Secondary school students	Quasi-experimental
Faizal Amir et al., 2024	Primary study	Higher education	45 university students	Quasi-experimental
Masti Yanto et al., 2025	Literature review	Mixed levels	Literature-based	Qualitative descriptive
Mohd Faisal Ibrahim et al., 2022	Primary study	Higher education	University dataset	Neural network modeling
Miftakhuddin et al., 2025a	Primary study	Higher education	University participants	Qualitative case study
S. C. Relmasira et al., 2025	Primary study	Primary education	118 students	Design-based research
Gisca Dea Sukma et	Primary	Secondary	61	Quantitative

al., 2025	study	education	respondents	survey
Iis Marsithah et al., 2024	Primary study	Higher education	Active university students	Quantitative survey
Azmy Ali Muchtar et al., 2025	Primary study	Secondary education	50 students	Quantitative survey
Lena et al., 2021	Primary study	Higher education	University students	Experiment (KNN)
Anindita Pratita et al., 2024	Primary study	Secondary education	3,405 population	SEM (UTAUT2)
Yohana Loisa Buton et al., 2025	Primary study	Secondary education	8 students	Quasi-experimental
Yosi Amelia Putri et al., 2025	Primary study	Higher education	281 respondents	Quantitative regression
Arini Alfa Mawaddah et al., 2025	Primary study	Higher education	9 university students	Qualitative phenomenology
Sri Umi Lestari et al., 2025	Needs analysis	Secondary education	30 students	Descriptive quantitative
Rimma Sianipar et al., 2025	Primary study	Higher education	20 university students	Mixed methods
Gilang Kurniawan et al., 2025	Primary study	Higher education	University participants	Experimental

Table 1 provides a structured overview of how artificial intelligence (AI) and learning analytics have been applied to support the learning proces in various contexts, ranging from PLS-SEM studies on personality and AI use to experimental approaches and data mining to predict student performance and adaptability. By organizing this evidence, the table establishes an empirical foundation for the subsequent analysis of AI tools and learning analytics approaches, prediction models and their accuracy, and their impact on self-regulation, motivation, and academic outcomes, which are discussed in the following subsections.

Artificial Intelligence (AI) and Learning Analytics Approaches

The reviewed studies used various AI technologies and learning analytics approaches to support teaching, learning, and assessment. Tools such as ChatGPT (Rasid et al., 2025), Gemini (Ardana et al., 2025), and various machine learning platforms (Arti et al., 2025) were used primarily for language-based assistance, prediction, and decision support in educational environments. Domain-specific applications such as Photomath for solving mathematics problems (Permatasari et al., 2021), FERMATA AI for music education (Jaohari et al., 2025), and Grammarly for writing support (Sianipar et al., 2025) show that AI adoption is not limited to general-purpose tools but also includes subject-oriented solutions.

Table 2. AI and Learning Analytics Approaches

CATEGORY	TOOLS	MAIN APPLICATIONS
Natural Language Processing	ChatGPT, Gemini, Copilot, Blackbox AI	Assignment assistance, concept explanation,

		feedback provision
Machine Learning Algorithms	Neural Networks, K-Nearest Neighbor, Decision Trees, Random Forest	Learning style prediction, performance prediction, adaptability assessment
Adaptive Learning Sytems	AI embedded in the platform (platform-embedded AI)	Personalized content delivery, real-timefeedback

Machine learning algorithms are widely applied in predictive analytics, particularly to estimate students' adaptability, learning styles, and academic performance. Neural networks achieved the highest reported accuracy, at 0.943, in predicting students' adaptability level (Arti et al., 2025), indicating strong potential for the early identification of students who may need additional support. The K-Nearest Neighbor (KNN) algorithm achieved 78% accuracy in predicting learning styles (Sumarlin et al., 2025) and 85% in predicting students' academic performance (Lena et al., 2021), suggesting that even relatively simple classifiers can still be effective in educational data mining contexts.

The learning management system (LMS) serves as the main integration platform where AI features are embedded to provide real-time feedback and personalization (Ibrahim et al., 2022). Through this platform, various AI tools are operationalized in everyday learning activities, enabling continuous monitoring of learners' learning behavior as well as adaptive adjustment of learning materials. Overall, these findings indicate a clear trend toward combining predictive models with embedded AI services to provide more responsive and individualized learning experiences.

Learning Analytics Implementation Approaches

The implementation of learning analytics in the reviewed studies varied from the use of standalone AI tools to solutions fully integrated within a learning management system (LMS). This approach is not only technical but also methodological, combining statistical modeling, data mining frameworks, and measurement models to capture the impact of AI on learning processes and outcomes.

Structural Equation Modeling with PLS is widely used to analyze the relationship between AI use and learning outcomes, allowing researchers to test complex causal pathways involving mediating and moderating variables (Rasid et al., 2025). The CRISP-DM methodology provides a structured framework for data mining workflows in predicting student adaptation, from problem understanding through systematic model evaluation (Arti et al., 2025). In parallel, the Rasch model is used to assess the effectiveness of AI-assisted interventions at various difficulty levels, enabling more precise evaluation of item and learner characteristics (Gautama et al., 2024).

The data sources used across these studies are highly diverse, reflecting both behavioral traces and self-reported perceptions. Examples include clickstream data from LMS interactions that record students' learning behavior over time (Ibrahim

et al., 2022), pre-test and post-test assessment data to measure improvements in learning outcomes (Prasetio et al., 2025), and behavioral and demographic data for profiling and prediction purposes (Sumarlin et al., 2025). Survey-based perception data are also used to capture students' and teachers' attitudes toward AI tools, complementing objective performance indicators (Dewi et al., 2025).

The level of automation in learning analytics systems lies on a continuum, from fully automated predictive models to collaborative human–AI approaches. Fully automated systems generate predictions or alerts with minimal human intervention, for example in adaptive recommendation or early warning scenarios (Arti et al., 2025). In contrast, collaborative human–AI implementations emphasize teacher involvement in interpreting analytic outputs and making pedagogical decisions, so that AI-generated insights can be contextualized within classroom practice (Prasetio et al., 2025).

Prediction Models and Accuracy

Table 3. Prediction Models

AUTHORS & YEAR	PREDICTION TYPE	ALGORITHM	PERFORMANCE	KEY VARIABLE
Shindy Arti et al., 2025	Adaptability level	Neural Network	0.943 accuracy	Gender, age, education level, class duration
Sumarlin Sumarlin et al., 2025	Learning style	K-Nearest Neighbor	78% accuracy	Final grade, predicate, study program, gender
Lena Lena et al., 2021	Student performance	KNN (k=3)	85% accuracy	Contextual information
Mohd Faisal Ibrahim et al., 2022	Learning style dimensions	Neural Networks	78–100% accuracy	LMS interaction records
Liina Parn et al., 2025	User experience	SEM	R^2 = 0.65	Content quality, interactivity, technology readiness
Sulaiman Abdul Rasid et al., 2025	Self-development	PLS-SEM	R^2 = 0.792	Personality traits, AI utilization
Desty Yani et al., 2025	Student performance	XGBoost, Random Forest	97.12% accuracy, 99.5% F-measure	Activity-related data

Recent studies show that applying machine learning algorithms to predict academic performance, learning behavior, and user experience yields consistently high accuracy. The Neural Network model used by Arti et al. (2025), for example, achieved an accuracy of 0.943 in predicting students' adaptability level based on demographic factors such as gender, age, education level, and class duration. This finding is in line with Ibrahim et al. (2022), who also used Neural Networks to identify learning style dimensions from LMS interaction records, with reported accuracy ranging from 78% to 100%.

Instance-based approaches such as K-Nearest Neighbor (KNN) also show competitive performance. Sumarlin et al. (2025) reported 78% accuracy in predicting learning styles using the variables of final grade, predicate, study program, and gender. Similarly, Lena et al. (2021) achieved 85% accuracy in predicting students' academic performance using KNN (k = 3) with contextual information as predictors.

Structural modeling techniques provide additional insights. Liina Parn et al. (2025) applied SEM and obtained an $R^2 = 0.65$ for modeling user experience, driven by the variables of content quality, interactivity, and technology readiness. Meanwhile, Rasid et al. (2025) used PLS-SEM and obtained an $R^2 = 0.792$ in predicting self-development, which was primarily influenced by personality traits and AI utilization.

Ensemble methods demonstrate the strongest predictive capability. Yani et al. (2025) reported 97.12% accuracy and a 99.5% F-measure when using XGBoost and Random Forest on learning activity data. In addition, the systematic review conducted by Yani et al. (2025) highlights that Random Forest is the most frequently used algorithm for academic performance prediction, with F-measures reaching up to 99.5%. Deep learning approaches, particularly RNN-LSTM, also show high performance with 97% accuracy and 98% AUC for sequential data analysis.

Impact on Self-Regulation and Metacognitive Development Quantitative Impact on Learning Independence

Table 4. Quantitative Impact

STUDY	MEASUREMENT	STATISTICAL RESULTS	SIGNIFICANCE
Nirmala Ardana et al., 2025	Learning independence	$\beta = 0.333$	$p = 0.011$
Sulaiman Abdul Rasid et al., 2025	Self-development	$\beta = 0.267$	$p < 0.05$
Sulaiman Abdul Rasid et al., 2025	Learning effectiveness	$\beta = 0.639$	$p < 0.05$
Asyhari A Usman et al., 2025	Learning independence score	Exp: 88.73, Ctrl: 78.90	$p < 0.05$
Supriadi Supriadi et al., 2025	Critical thinking	$F(2,26) = 65.14$, $\eta^2 = 0.95$	$p = 0.021$
Ginati Ayuningtyas et al., 2024	Critical thinking	53.2% contribution	$p < 0.001$
Yosi Amelia Putri et al., 2025	Self-efficacy	$R^2 = 0.489$	Significant

Empirical evidence from various studies shows a consistent pattern: learning interventions and learner characteristics significantly improve students' self-regulation and metacognitive development. Ardana et al. (2025) reported a positive and significant effect on learning independence ($\beta = 0.333$; $p = 0.011$), indicating that the intervention meaningfully strengthened university students' independent

learning skills. This finding is consistent with the experimental results of Usman et al. (2025), in which the experimental group obtained a higher learning independence score (88.73) than the control group (78.90) with statistical significance ($p < 0.05$). Taken together, these results illustrate a consistent improvement in learners' self-regulatory behavior, in both correlational and experimental studies.

Further evidence from Rasid et al. (2025) strengthens the argument about the role of individual characteristics and AI utilization in supporting developmental outcomes. Their findings show a significant effect on self-development ($\beta = 0.267$; $p < 0.05$) and an even stronger effect on learning effectiveness ($\beta = 0.639$; $p < 0.05$), indicating that cognitive and behavioral performance is substantially shaped by these factors.

Metacognitive development is also supported through improved critical thinking skills, which are a core component of higher-order cognition. Supriadi et al. (2025) reported a large effect on critical thinking skills, with $F(2,26) = 65.14$, $\eta^2 = 0.95$, and $p = 0.021$, indicating a very strong influence. Complementarily, Ayuningtyas et al. (2024) found that critical thinking accounted for 53.2% of the variation in the observed outcomes ($p < 0.001$). Together, these results imply that the learning interventions and contexts examined in these studies strengthen learners' evaluative and analytical abilities, which underpin metacognitive regulation.

In addition, Yosi Amelia Putri et al. (2025) reported that self-efficacy could be significantly predicted in the model they developed, with an $R^2 = 0.489$, indicating that almost half of the variance in self-efficacy can be explained by the factors examined. Given that self-efficacy is closely related to self-regulation, this finding further reinforces the general tendency seen across studies that certain interventions and characteristics consistently contribute to strengthening learners' self-regulation.

Improvement in Academic Achievement

Table 5. Improvement Results

STUDY	CONTEXT	PERFORMANCE ASSESSMENT	RESULTS	SIGNIFICANCE
Satunggale Kurniawan et al., 2025	Adaptive learning media	Final exam score	23.5% increase	Significant
Annas Prasetio et al., 2025	AI chatbot intervention	Academic score	15.7% increase	$p < 0.05$
Masti Yanto et al., 2025	AI-based personalization	Learning outcomes	15% increase	Significant
Yohana Loisa Buton et al., 2025	GPT AI in mathematics	Average score	65 → 91.25 (40.38% increase)	Significant

Faizal Amir et al., 2024	AI-based pre-learning organizer	Final exam score	Exp: 60.72, Ctrl: 45.65;N-Gain: 0.599 vs 0.036	Significant
Azmy Ali Muchtar et al., 2025	AI-based learning platform	Academic grades	70 → 80	$p < 0.05$
Iis Marsithah et al., 2024	AI-based learning	Academic performance	45% increase per usage increment; Regression = 0.45	Significant
Muttaqin Kholis Ali et al., 2025	AI-based media	Conceptual understanding	15–25% increase	Significant

Consistent evidence from various recent studies shows that AI-based learning interventions significantly improve students' academic performance across diverse educational contexts. Kurniawan et al. (2025) reported a 23.5% increase in post-test scores through adaptive learning media, indicating that personalized content delivery can meaningfully improve mastery of learning material. Similarly, Prasetio et al. (2025) found that an AI-based chatbot intervention increased academic grades by 15.7% with statistical significance ($p < 0.05$), implying that interactive AI feedback strengthens understanding and knowledge retention.

This positive impact of personalization is further reinforced by the findings of Yanto et al. (2025), who recorded a 15% increase in learning outcomes through AI-based personalization, affirming the role of adaptive learning pathways in optimizing student learning. An even greater improvement was reported by Loisa Buton et al. (2025), in which the application of GPT-based AI in mathematics learning raised the average score from 65 to 91.25, equivalent to a 40.38% increase with significant results. These findings highlight the transformative potential of AI-generated explanations and problem-solving assistance in complex fields of study.

Experimental evidence further strengthens this trend. Amir et al. (2024) showed that AI-assisted advance organizers produced higher performance on the post-test in the experimental group (60.72) compared with the control group (45.65), supported by a large difference in N-Gain scores (0.599 vs 0.036). This indicates that structured AI-generated scaffolding can substantially improve students' concept acquisition. Additional improvements in academic grades were also reported by Muchtar et al. (2025), in which the use of an AI-based learning platform raised scores from 70 to 80 ($p < 0.05$). In line with this, Marsithah et al. (2024) found that AI-based learning increased academic performance by 45% per increase in usage frequency, supported by a regression coefficient of 0.45 and reflecting a strong linear relationship between AI utilization and academic achievement.

Finally, Kholis Ali et al. (2025) documented a 15–25% improvement in conceptual understanding through AI-based media, affirming that AI tools

effectively support higher-level understanding and the formation of better-structured knowledge.

Impact on Motivation and Engagement

Table 6. Impact on Motivation and Engagement

AUTHORS & YEAR OF PUBLICATION	VARIABLE	FINDINGS
Masti Yanto et al., 2025	Learning motivation	20% increase
Azmy Ali Muchtar et al., 2025	Motivation with AI platform	84% of students reported increased motivation
Iis Marsithah et al., 2024	Student engagement	68% increase in participation
Muhamad Rizki Suryawijaya et al., 2025	Learning motivation	75% reported a positive impact
Syamsidar Hs et al., 2024	Confidence in completing tasks	38% strongly agree, 34% agree

Findings from various recent studies consistently show that AI-supported learning environments have a substantial positive impact on student motivation and engagement. Yanto et al. (2025) reported a 20% increase in learning motivation, indicating that AI-based personalization can effectively stimulate students' interest and persistence in the learning process. This increase in motivation was also seen in the study by Muchtar et al. (2025), in which 84% of students reported higher motivation when using an AI-based learning platform, indicating that AI's interactive features help create a more supportive and engaging learning atmosphere.

The influence of AI tools extends beyond motivation by significantly increasing student engagement. Marsithah et al. (2024) documented a 68% increase in student participation, implying that AI-based learning environments successfully encourage active engagement and reduce passive learning behavior. This kind of increased engagement reflects AI systems' ability to provide timely feedback, adaptive challenges, and personalized learning pathways. Learners' perceptions further reinforce these findings. Suryawijaya et al. (2025) found that 75% of students reported a positive impact of AI on their learning motivation, highlighting broad acceptance and the psychological benefits of AI-enriched learning. In addition, Syamsidar et al. (2024) reported high levels of confidence during task completion, with 38% of students strongly agreeing and 34% agreeing that the AI-assisted approach increased their self-confidence. This suggests that AI contributes not only to increased motivation but also to the development of students' confidence and readiness in facing tasks.

Self-Regulation and Metacognitive Skill Development

The integration of AI technology has been shown to have a considerable impact on students' self-regulation development, encompassing cognitive, affective, and behavioral dimensions. Through automated feedback and personalized recommendations, AI increases learners' self-awareness of their progress and

performance (Dewi et al., 2025). This heightened awareness encourages students to reflect more deeply on their learning processes and outcomes, thereby forming a foundation for better self-regulatory behavior.

Beyond awareness, AI-assisted learning environments also strengthen students' ability to set realistic goals and choose effective learning strategies according to their needs (Ardana et al., 2025). The technology provides continuous scaffolding to support adaptive decision-making, enabling students to take greater ownership of their learning pathways. Real-time formative assessment embedded in AI systems further fosters monitoring and self-assessment skills, so that students can identify gaps and make timely learning adjustments (Kurniawan et al., 2025).

Several studies highlight increased autonomy and independence as a primary outcome of integrating AI into learning (Gautama et al., 2024). Reduced reliance on direct guidance from teachers reflects a shift toward more self-directed learning behavior, in which students show confidence and initiative in managing their own progress. In music education, for example, the FERMATA AI system plays an important role in developing personal awareness by helping students understand their musical identity and design professional development strategies more effectively (Jaohari et al., 2025).

Beyond the realm of self-regulation, AI integration also contributes substantially to the development of metacognitive skills, particularly in fostering critical thinking. Among educational technology students, AI-assisted systems were reported to account for 53.2% of the observed improvement in critical thinking skills (Ayuningtyas et al., 2024). Similarly, AI-based learning media showed a large effect size ($\eta^2 = 0.95$) in improving critical thinking in the context of civic education (Supriadi et al., 2025). These findings indicate that AI not only supports regulation of one's own learning processes but also encourages higher-order cognitive processes that are essential for reflective and analytical thinking.

Digital Learning

Table 7. Digital Learning Level Results

Component	Description	Level
Platform Type	Web-based systems (Ardana et al., 2025), LMS-embedded (Ibrahim et al., 2022), Mobile apps (Permatasari et al., 2021)	High
Learning Modality	Blended learning (Usman et al., 2025), Fully online (Santosa et al., 2020), Face-to-face with digital tools (Sianipar et al., 2025)	Mixed
Personalization Features	Adaptive content delivery (Kurniawan et al., 2025), Learning path customization (Amanullah et al., 2025), Preference mapping	High

	(Kurniawan et al., 2025)	
Real-time Feedback	Automatic performance feedback (Kurniawan et al., 2025), Grammar and style correction (Sianipar et al., 2025), Chatbot responses (Prasetio et al., 2025).	High
Collaborative Features	Teacher dashboard analytics (Sianipar et al., 2025), Discussion forums (Ibrahim et al., 2022), Peer interaction platforms (Amanullah et al., 2025).	Moderate

The digital learning systems developed in the various studies show the integration of several key components that play an important role in improving the effectiveness and flexibility of the learning process. Each component has different characteristics and varying levels of implementation, which together reflect the direction of modern educational technology development. In terms of Platform Type, the implementation level is categorized as High, indicating that platform design serves as the main foundation in developing digital learning systems. Various forms of platforms are used, including web-based systems (Ardana et al., 2025), platforms integrated within an LMS (Ibrahim et al., 2022), and mobile applications (Permatasari et al., 2021). This diversity gives learners flexibility of access across devices and learning contexts, both formal and informal. This flexibility reflects a deliberate effort to broaden learning access while maintaining user convenience.

The next component, Learning Modality, shows a Mixed level of implementation, which illustrates the diversity of approaches in applying educational technology. Previous research identified several frequently used models, such as blended learning that combines online and face-to-face sessions (Usman et al., 2025), fully online learning conducted through digital platforms (Santosa et al., 2020), and face-to-face learning enriched with digital technology (Sianipar et al., 2025). This variation shows that educational institutions continue to adjust their pedagogical strategies to learners' needs and technological readiness.

Furthermore, the Personalization Features component achieved a High level of implementation because of its significant contribution to improving individual learning experiences. The developed systems are able to tailor content to learners' abilities and preferences through adaptive content delivery (Kurniawan et al., 2025), provide flexibility in designing learning paths through learning path customization (Amanullah et al., 2025), and recognize learning styles and preferences through preference mapping (Kurniawan et al., 2025). Through these personalization mechanisms, learning becomes more relevant, efficient, and learner-centered, in line with the principles of adaptive and individualized education.

The Real-time Feedback component also shows a High level of implementation. This component plays an important role in ensuring that learners

receive fast and meaningful feedback during the learning process. Features such as automatic performance feedback (Kurniawan et al., 2025), grammar and writing style correction (Sianipar et al., 2025), and chatbot-based interaction (Prasetio et al., 2025) illustrate technology's ability to provide fast and accurate learning support. By providing immediate responses, these systems help learners correct mistakes quickly and effectively strengthen their understanding.

Meanwhile, Collaborative Features are at a Moderate level of implementation, indicating that digital collaboration is still in the development stage but has great potential. These features include teacher analytics dashboards for monitoring students' learning progress (Sianipar et al., 2025), discussion forums as spaces for interaction and reflection (Ibrahim et al., 2022), and peer interaction platforms that foster cooperative and community-based learning (Amanullah et al., 2025). Although not yet as intensive as the other components, collaborative tools are an important element in strengthening the social dimension of digital learning environments.

Overall, current digital learning systems show strong development in components with a high level of implementation, such as flexible platforms, adaptive personalization features, and effective real-time feedback mechanisms. However, the collaborative aspect still requires further improvement to support a more interactive and participatory learning environment. A balanced integration of all these components forms the foundation for an effective, adaptive, and sustainable digital learning ecosystem.

CONCLUSION

This systematic review synthesizes evidence from 34 empirical and review studies examining how AI-based learning analytics systems affect self-regulation, metacognitive development, and academic outcomes in primary, secondary, and higher education. The findings show that various AI tools—from predictive models, adaptive learning systems, and chatbots to generative AI—consistently support key SRL processes such as monitoring, strategy use, and goal setting, while also increasing motivation, engagement, and academic performance when aligned with sound pedagogical design; at the same time, substantial challenges remain, such as technical and infrastructure limitations, limited teacher readiness, ethical and privacy issues, and the risk of over-reliance that can weaken critical and metacognitive thinking if left unmanaged. Overall, this review affirms that AI-based learning analytics has strong potential to foster self-regulation, but its effectiveness depends heavily on careful integration into teaching practice, robust institutional and policy support, and a design that deliberately positions AI as a support for learner agency, not a replacement for human judgment.

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