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AI-Driven Learning Analytics for Self-Regulated and Metacognitive Learning: A Systematic Review

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A B S T R A C T

Artificial intelligence (AI) and learning analytics are increasingly integrated into educational systems, yet their impact on self-regulated learning (SRL) and metacognition remains not fully understood. This systematic review synthesizes findings from 34 empirical and review studies on AI-driven learning analytics in formal education, focusing on their effects on SRL, metacognition, motivation, and academic performance. Following PRISMA guidelines, studies were identified through searches in Scopus, Web of Science, ERIC, and Google Scholar for articles published between 2020 and 2025, using keywords related to AI, learning analytics, SRL, and metacognition. Studies were included if they used AI-based analytical or adaptive systems, standardized SRL or metacognitive measures, and pre–post or comparison data. Results show that AI-based tools such as predictive models, intelligent tutoring systems, adaptive platforms, learning dashboards, and generative or conversational AI support goal setting, monitoring, strategy adjustment, and reflective evaluation through feedback, progress visualization, and personalized recommendations. Most studies report improvements in SRL strategies, metacognitive awareness, motivation, engagement, and learning outcomes, though effects vary across research design quality, educational levels, and subject areas. However, several challenges persist, including infrastructural limitations, limited teacher readiness, data privacy and ethical issues, algorithmic bias, and potential overreliance on AI that may weaken learners' independent strategic thinking. Overall, AI-driven learning analytics hold substantial potential to enhance SRL and metacognition when integrated within coherent pedagogical frameworks and supported by institutional policies promoting transparency, equity, and human agency.

Abstrak

Kecerdasan buatan (AI) dan learning analytics semakin meluas dalam sistem pendidikan, namun dampaknya terhadap self-regulated learning (SRL) dan metakognisi masih belum sepenuhnya dipahami. Tinjauan sistematis ini mensintesis temuan dari 34 studi empiris dan tinjauan pustaka mengenai penerapan AI-driven learning analytics di pendidikan formal, berfokus pada pengaruhnya terhadap SRL, metakognisi, motivasi, dan kinerja akademik. Dengan mengikuti pedoman PRISMA, artikel dipilih melalui pencarian di Scopus, Web of Science, ERIC, dan Google Scholar untuk periode 2020–2025 menggunakan kata kunci terkait AI, learning analytics, SRL, dan metakognisi. Studi disertakan jika menggunakan sistem analitik atau adaptif berbasis AI dengan instrumen terstandar dan data perbandingan pre–post. Hasil menunjukkan bahwa alat berbasis AI seperti model prediktif, sistem tutor cerdas, platform adaptif, dashboard pembelajaran, serta AI generatif atau konversasional mendukung penetapan tujuan, pemantauan, adaptasi strategi, dan refleksi melalui umpan balik, visualisasi kemajuan, dan rekomendasi otomatis. Sebagian besar studi melaporkan peningkatan strategi SRL, kesadaran metakognitif, motivasi, keterlibatan, dan hasil belajar, meski efek berbeda bergantung pada desain penelitian, jenjang pendidikan, dan bidang studi. Namun, tantangan tetap muncul, termasuk keterbatasan infrastruktur, kesiapan guru, privasi data, bias algoritmik, serta potensi ketergantungan berlebih pada AI yang dapat melemahkan kemandirian berpikir strategis. Secara keseluruhan, AI-driven learning analytics berpotensi memperkuat SRL dan metakognisi bila diintegrasikan dalam kerangka pedagogis yang jelas dan didukung kebijakan institusional yang menegakkan transparansi, keadilan, dan agensi manusia.

1. Introduction

Artificial Intelligence (AI) has become a central driver of innovation in education, reshaping how learning is designed, delivered, and evaluated across disciplines and educational levels. Recent systematic and scoping reviews document a rapid expansion of AI-enhanced systems, including intelligent tutoring, adaptive platforms, and predictive analytics that aim to personalize instruction and support decision making in complex learning environments [1]. This expansion spans multiple domains such as higher education, medical and special education, and broader technology-enhanced learning, reflecting the growing expectation that AI will play a structural role in future educational ecosystems [2].

In parallel, self-regulated learning (SRL) has been increasingly emphasized as a core competence for learners navigating digital and online environments. SRL captures learners' abilities to set goals, select strategies, monitor progress, and reflect on outcomes, and has been identified as critical for success in e-learning and blended settings [3], [4]. Systematic reviews on SRL in the digital age highlight that students increasingly rely on a combination of cognitive, metacognitive, and motivational strategies to manage their learning, but also that many struggle to maintain effective regulation without targeted support [5], [6]. These observations position SRL as a natural focal point for understanding how AI might not only deliver content but also shape learners' agency and autonomy over time [3], [5].

Within this broader landscape, AI technologies are increasingly deployed to scaffold specific SRL processes rather than functioning solely as content delivery tools. Qualitative and systematic reviews in higher education show that AI-empowered environments can prompt learners to plan their study activities, monitor their performance, and adjust strategies based on adaptive feedback and analytics-based insights [7]. Learning analytics dashboards and recommendation systems help students track progress, manage time, and identify at-risk patterns, thereby supporting the behavioral and monitoring dimensions of SRL in online and MOOC contexts [6]. At the same time, research on educational chatbots indicates that conversational agents can assist with resource identification and real-time clarification of understanding in self-paced learning scenarios, extending SRL support into everyday interactions with learning platforms [8], [9].

More recently, generative and conversational AI have been conceptualized as cognitive partners that can influence learners' metacognitive and reflective practices. Systematic reviews report that generative AI can provide tailored explanations, hints, and reflective prompts that encourage students to articulate reasoning, compare alternative solutions, and revise their understanding, with emerging evidence of positive effects on self-regulated learning and critical thinking [10], [11]. Studies on AI-enhanced autonomous learning in vocational and higher education further suggest that AI-driven systems may support goal setting and strategy selection by offering structured pathways and personalized recommendations [12] In addition, work on AI-mediated metacognitive and emotional support underscores that AI can be integrated into broader frameworks targeting psychological and reflective dimensions of learning, not only cognitive performance [13].

Despite these promising developments, the literature also highlights substantial risks and unresolved tensions in how AI shapes SRL. Reviews of AI-supported learning environments caution that poorly structured 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 answer-providing tool [11]. Ethical and equity concerns add further complexity, as studies on AI in online and language learning point to challenges related to data privacy, algorithmic bias, and uneven access to AI-rich infrastructures, which may differentially impact learners' capacity to exercise self-regulation [9]. At the same time, analyses of AI in medical and special education show that domain-specific implementations raise unique questions about transparency, trust, and appropriate levels of automation in high-stakes learning contexts [14].

Research on AI, learning analytics, and SRL has expanded rapidly since 2020 but remains fragmented [13], [15] Existing reviews examine isolated strands: intelligent tutoring systems [16], AI in medical/special education [14], generative AI assessment practices [17], or domain-specific applications. Critically, comprehensive synthesis systematically maps AI-driven learning analytics tools, the specific SRL/metacognitive subprocesses they target, their effects on motivation and performance, and the implementation mechanisms/conditions that mediate outcomes across formal education levels (K-12 through higher education) [15].

This systematic review addresses this gap by synthesizing evidence from 34 empirical studies on AI-driven learning analytics in formal education settings. (1) map AI-driven learning analytics tools (predictive models, intelligent tutoring systems, dashboards, generative AI) and their targeted SRL/metacognitive processes; (2) synthesize reported effects on SRL skills, metacognitive awareness, motivation, engagement, and academic performance; and (3) identify implementation mechanisms, enabling conditions, and challenges explaining heterogeneous findings and sustainability concerns.

2. Methods

This systematic literature review followed PRISMA 2020 guidelines to synthesize evidence on AI-driven learning analytics—defined as learning analytics incorporating machine learning, predictive modeling, or adaptive algorithms to analyze learner data and deliver personalized SRL support, distinguishing them from descriptive analytics.

Literature search from databases in Scopus, Web of Science, ERIC, and Google Scholar, covering peer-reviewed articles published between 2020 and 2025 in Indonesian or English. The search keywords combined terms related to artificial intelligence (“artificial intelligence,” “machine learning,” “predictive models,” “generative artificial intelligence”), learning analytics (“learning analytics,” “educational data mining,” “dashboard”), SRL (“self-regulated learning,” “self-regulation,” SRL), and metacognition (“metacognition,” “self-awareness,” “self-monitoring”), yielding 1,400 records.

Inclusion criteria required: (1) students in formal education (K-12, higher education, vocational training); (2) AI-driven learning analytics interventions analyzing learner data for SRL/metacognitive support; (3) standardized SRL/metacognitive measures (e.g., MSLQ, Metacognitive Awareness Inventory) with empirical pre-post/comparison data; and (4) peer-reviewed empirical or review studies 2020-2025. Exclusion criteria eliminated theoretical papers, non-AI tools, informal learning contexts, and studies lacking standardized measures.

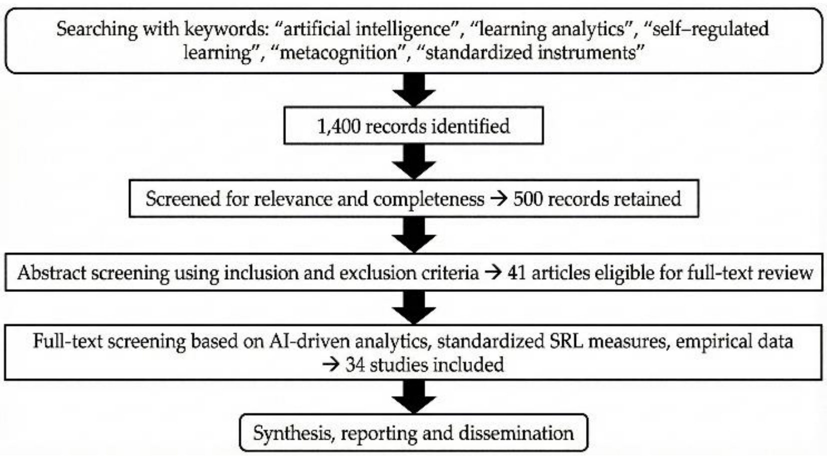

Figure 1. PRISMA 2020 Flow Diagram of Study Selection

From 1,400 records identified through database searching using keywords "artificial intelligence," "learning analytics," "self-regulated learning," and "metacognition/standardized instruments," 500 records were retained after relevance screening. Abstract screening based on inclusion criteria (AI-driven analytics, standardized SRL measures, empirical data) yielded 41 articles eligible for full-text review.

Full-text screening based on AI-driven interventions, standardized SRL measures, and empirical designs resulted in 34 studies included in the synthesis, reporting, and dissemination.

Table 1. MMAT Quality Appraisal Summary

Study Type	n	High Quality	Moderate	Low
Quantitative	22	14 (64%)	7 (32%)	1 (4%)
Qualitative	6	3 (50%)	3 (50%)	0
Mixed Methods	6	3 (50%)	2 (33%)	1 (17%)
Systematic Reviews	4	3 (75%)	1 (25%)	0
R&D/Design-based	2	1	1	0
TOTAL	34	21 (62%)	10 (29%)	3 (9%)

Quality appraisal used Mixed Methods Appraisal Tool (MMAT) 2018 across quantitative (n=22), qualitative (n=6), and mixed methods (n=6) designs. Overall quality was high (≥80%, n=21), moderate (50-79%, n=10), and low (<50%, n=3; mean score 78%). Low-quality studies were weighted cautiously during synthesis.

Data extraction covered study characteristics, AI-driven learning analytics details (tool type, features, data sources), SRL/metacognitive instruments, effects on SRL/metacognition/motivation/performance, and proposed mechanisms. Synthesis employed narrative synthesis with thematic analysis, organizing findings into three themes aligned with review aims: (1) AI tools and targeted SRL/metacognitive processes, (2) reported effects and outcomes, and (3) implementation mechanisms, conditions, and challenges. Tabular summaries and vote-counting by effect direction supplemented the narrative synthesis.

3. Result and Discussion

3.1. Result

Based on the systematic review process described in the Method section, the final corpus comprises 34 empirical and review studies on AI-driven learning analytics and self-regulated learning across primary, secondary, and higher education. The key characteristics of these studies are summarized in Tabel 2, including author and year, study type, educational level, population, and methodological approach.

Table 2. Summary of studies reviewed

Authors (Year)	Study Type	Level	AI/LA Type	SRL Measure	Design	Main Outcome	Quality
Sulaiman et al. (2025)	Primary	Higher	Predictive	MSLQ	PLS-SEM	Self-dev R^2=0.792 ↑	High
Amanullah (2025)	SLR	Secondary	Adaptive	Lit review	Theory synth	SRL framework	High
Lazaro Dewi (2025)	Primary	Higher	ML	Self-report	Quant desc	Independence ↑	Mod
Eka Budhi (2020)	Primary	Higher	Clustering	Self-report	K-means	Style pred 78%	Mod
B.P. Gautama (2024)	Primary	Higher	Predictive	Rasch	Rasch model	Performance ↑	High
Shindy Arti (2025)	Primary	Higher	Neural Net	Adaptability	CRISP-DM	94.3% accuracy ↑	High
Nirmala Ardana (2025)	Primary	Higher	Predictive	Independence	Regression	β=0.333 ↑	High
Satunggale (2025)	R&D	Secondary	Adaptive	Self-report	Borg & Gall	Scores +23.5% ↑	Mod
Enry Jaohari (2025)	Primary	Higher	Generative	Qual scales	Qual desc	Motivation ↑	Mod
Asyhari Usman (2025)	Primary	Secondary	Adaptive	Independence	Quasi-exp	+9.83 pts ↑	High

Authors (Year)	Study Type	Level	AI/LA Type	SRL Measure	Design	Main Outcome	Quality
Selviana (2023)	Primary	Higher	Mixed ML	Mixed scales	Mixed	Engagement ↑	Mod
Miftakhuddin (2025)	Primary	Higher	Predictive	MSLQ	Mixed	Framework ↑	High
Christine (2021)	Primary	Secondary	Generative	Qual	Qual desc	Understanding ↑	Low
Liina Parn (2025)	Primary	Higher	SEM	Experience	SmartPLS	R^2=0.65 ↑	High
Sumarlin (2025)	Primary	Higher	ML comp	Style	ML	78% accuracy ↑	High
M. Fadhilah (2025)	SLR	Primary	Lit review	Lit-based	PRISMA	Literacy ↑	High
Annas Prasetio (2025)	Primary	Secondary	Chatbot	Scores	Mixed	+15.7% ↑	Mod
Rizki Suryaw (2025)	Primary	Higher	Qual	Motivation	Qual desc	75% positive ↑	Mod
Syamsidar Hs (2024)	Primary	Higher	Survey	Confidence	Quant surv	38% strong agree	Mod
Desty Yani (2025)	SLR	Mixed	Ensemble	Performance	SLR	97.12% ↑	High
Supriadi (2025)	Primary	Secondary	Media	Crit thinking	Quasi-exp	η^2=0.95 ↑	High
Sukarman Purba (2025)	Primary	Higher	Survey	Performance	Quant surv	Grades 70→80 ↑	Mod
Ginati (2024)	Primary	Higher	Quant	Crit thinking	Quant desc	53.2% ↑	High
Muttaqin (2025)	Primary	Secondary	Media	Understanding	Quasi-exp	+15-25% ↑	High
Faizal Amir (2024)	Primary	Higher	Organizer	Post-test	Quasi-exp	N-Gain 0.599 ↑	High
Masti Yanto (2025)	Lit review	Mixed	Personal	Outcomes	Qual desc	+15% ↑	Mod
Mohd Faisal (2022)	Primary	Higher	Neural	Style	NN	78-100% ↑	High
Miftakhuddin (2025a)	Primary	Higher	Case	Qual	Case study	Framework ↑	Mod
S.C. Relmasira (2025)	Primary	Primary	DBR	Literacy	Design-based	Diff ↓46→16%	Mod
Gisca Dea (2025)	Primary	Secondary	Survey	Survey	Quant surv	Motivation ↑	Mod
Iis Marsithah (2024)	Primary	Higher	AI learn	Performance	Quant surv	+45%/usage ↑	High
Azmy Muchtar (2025)	Primary	Secondary	Platform	Grades	Quant surv	70→80 ↑	Mod
Lena (2021)	Primary	Higher	KNN	Performance	Exp KNN	85% ↑	High
Anindita (2024)	Primary	Secondary	SEM	Adoption	SEM	UTAUT2 ↑	High
Yohana Loisa (2025)	Primary	Secondary	GPT math	Scores	Quasi-exp	65→91 ↑	High

Tabel 2 provides a structured overview of how AI and learning analytics have been implemented to support learning processes in different contexts, ranging from PLS-SEM studies on personality and AI use to experimental and data-mining approaches for predicting student performance and adaptability. By organizing the evidence in this way, the table establishes the empirical foundation for the subsequent analysis of AI tools and learning analytics approaches, prediction models and accuracy, and their effects on self-regulation, motivation, and academic outcomes discussed in the following subsections.

3.1.1. AI and Learning Analytics Approaches

The reviewed studies employed a wide spectrum of AI technologies and learning analytics approaches to support teaching, learning, and assessment. Tools such as ChatGPT [18], Gemini [19], and various machine learning platforms [20] were used primarily for language-based assistance, prediction, and decision support in educational settings. Domain-specific applications such as Photomath for mathematical problem-solving [21], FERMATA AI for music education [22], and Grammarly for writing support [23] indicate that AI adoption is not limited to general-purpose tools, but also extends to subject-oriented solutions.

Table 3. Categories of AI approaches and tools used

Category	n (%)	Examples	LA Features
Predictive Analytics	15 (44%)	Neural Nets [20], KNN [24]	LMS data → perf/adapt pred
Adaptive Dashboards	11 (32%)	LMS feedback [25]	Behavior → recs
Generative Assist.	8 (24%)	ChatGPT [26], GPT math [27]	NLP → prompts

Machine learning algorithms were extensively applied for predictive analytics, particularly for estimating students' adaptability, learning styles, and academic performance. Neural networks achieved the highest reported accuracy of 0.943 in predicting student adaptability levels [20], suggesting strong potential for early identification of students who may require additional support. The K-Nearest Neighbor algorithm reached 78% accuracy in learning style prediction [28] and 85% accuracy in student performance prediction [24], indicating that relatively simple classifiers can still be effective in educational data mining contexts.

Learning management systems (LMS) functioned as the primary integration platforms where AI features are embedded for real-time feedback and personalization [29]. Through these platforms, AI tools are operationalized in everyday learning activities, enabling continuous monitoring of learner behavior and adaptive adjustment of learning materials. Overall, the findings show a clear trend toward combining predictive models with embedded AI services to provide more responsive and individualized learning experiences.

3.1.2. Learning Analytics Implementation Approaches

Learning analytics implementations in the reviewed studies ranged from the use of standalone AI tools to fully integrated solutions embedded within learning management systems (LMS). Implementations were 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 was commonly employed to analyze the relationships between AI use and learning outcomes, allowing researchers to test complex causal paths involving mediating and moderating variables [18]. The CRISP-DM methodology provided a structured framework for data mining workflows in student adaptation prediction, ensuring systematic steps from problem understanding to model evaluation [20]. In parallel, the Rasch model was used to assess the effectiveness of AI-supported interventions across different difficulty levels, enabling more precise evaluation of item and learner characteristics [30].

Data sources utilized across the studies were diverse, reflecting both behavioral traces and self-reported perceptions. These included clickstream data from LMS interactions that captured students' learning behaviors over time [29], assessment data from pre- and post-tests to measure learning gains [26], as well as behavioral and demographic data for profiling and prediction purposes [28]. Survey-based perceptual data were also used to capture students' and teachers' attitudes toward AI tools, complementing objective performance indicators [31].

The level of automation in learning analytics systems ranged on a continuum from fully automated predictive models to human–AI collaborative approaches. Fully automated systems generated predictions or alerts with minimal human intervention, for example in adaptive recommendation or early-warning scenarios [20]. In contrast, human AI collaborative implementations emphasized teacher involvement in interpreting analytics outputs and making pedagogical decisions, ensuring that AI-generated insights were contextualized within classroom practices [26].

3.1.3. Prediction Models and Accuracy

Table 4. Prediction Models and Accuracy

Authors & Year	Prediction Type	Algorithm	Performance	Key Variable
[20] Shindy Arti et al., 2025	Adaptability level	Neural Network	0.943 accuracy	Gender, age, education level, class duration
[28] Sumarlin Sumarlin et al., 2025	Learning style	K-Nearest Neighbor	78% accuracy	Final grade, predicate, study program, gender
[24] Lena et al., 2021	Student performance	KNN (k=3)	85% accuracy	Contextual information
[29] Ibrahim et al., 2022	Learning style dimensions	Neural Networks	78–100% accuracy	LMS interaction records
[32] Liina Parn et al., 2025	User experience	SEM	$R^2 = 0.65$	Content quality, interactivity, technology readiness
[18] Rasid et al., 2025	Self-development	PLS-SEM	$R^2 = 0.792$	Personality traits, AI utilization
[33] Desty Yani et al., 2025	Student performance	XGBoost, Random Forest	97.12% accuracy, 99.5% F-measure	Activity-related data

Recent studies demonstrate that machine learning applications for predicting student performance, learning behavior, and user experience have reached consistently high levels of accuracy. The Neural Network model employed by [20], for example, achieved an accuracy of 0.943 in predicting adaptability levels based on demographic factors such as gender, age, education level, and class duration. This finding aligns with [29], who also used Neural Networks to identify learning style dimensions from LMS interaction records, reporting accuracies ranging from 78% to 100%.

Instance-based approaches such as K-Nearest Neighbor (KNN) also demonstrate competitive performance. [28] reported 78% accuracy in predicting learning styles using variables including final grade, predicate, study program, and gender. Similarly, [24] achieved 85% accuracy in predicting student performance using KNN (k = 3) and contextual information as predictors.

Structural modeling techniques reveal additional insights. [32] applied SEM and obtained $R^2 = 0.65$ to model user experience, driven by key variables such as content quality, interactivity, and technology readiness. Meanwhile, [18] employed PLS-SEM and achieved $R^2 = 0.792$ in predicting self-development, influenced primarily by personality traits and AI utilization.

Ensemble learning methods show the strongest predictive capabilities. [33] reported 97.12% accuracy and a 99.5% F-measure using XGBoost and Random Forest on activity-related data. Furthermore, the systematic review conducted by [33] highlighted Random Forest as the most frequently used algorithm for student performance prediction, achieving F-measure scores up to 99.5%. Deep learning approaches, particularly RNN-LSTM, also demonstrated strong performance with 97% accuracy and 98% AUC for sequential data analysis.

3.1.4. Effects on Self-Regulation and Metacognitive Development

3.1.4.1. Quantitative Effects on Learning Independence

Table 5. The relationship between AI/LA and SRL outcomes and metacognition

Study	Outcome Measure	Statistical Result	Significance
[19] Nirmala Ardana et al., 2025	Learning independence	$\beta = 0.333$	$p = 0.011$
[18] Rasid et al., 2025	Self-development	$\beta = 0.267$	$p < 0.05$
[18] Rasid et al., 2025	Learning effectiveness	$\beta = 0.639$	$p < 0.05$
[34] Usman et al., 2025	Learning independence score	Exp: 88.73, Ctrl: 78.90	$p < 0.05$
[35] Supriadi et al., 2025	Critical thinking	$F(2,26) = 65.14$, $\eta^2 = 0.95$	$p = 0.021$
[36] Ayuningtyas et al., 2024	Critical thinking	53.2% contribution	$p < 0.001$
[37] Yosi Amelia Putri et al., 2025	Self-efficacy	$R^2 = 0.489$	Significant

Empirical evidence from multiple studies shows a consistent pattern indicating that learning interventions and learner characteristics significantly enhance students' self-regulation and metacognitive development. [19] reported a positive and significant effect on learning independence ($\beta = 0.333$, $p = 0.011$), demonstrating that the intervention meaningfully strengthened students' autonomous learning skills. This finding aligns with the experimental results of [34], where the experimental group achieved a higher learning independence score (88.73) compared to the control group (78.90), with statistical significance ($p < 0.05$). Together, these results illustrate a consistent improvement in learners' self-regulatory behavior across both correlational and experimental designs.

Further evidence from [18] strengthens the argument for the role of individual traits and AI utilization in supporting developmental outcomes. Their findings indicate significant effects on self-development ($\beta = 0.267$, $p < 0.05$) and an even stronger impact on learning effectiveness ($\beta = 0.639$, $p < 0.05$), suggesting that cognitive and behavioral performance is substantially shaped by these contributing factors.

Metacognitive development is also supported through improvements in critical thinking ability, a core component of higher-order cognition. [35] reported a large effect on critical thinking with $F(2,26) = 65.14$, $\eta^2 = 0.95$, and $p = 0.021$, indicating a highly robust influence. Complementarily, [36] found that critical thinking accounted for 53.2% of the observed outcomes ($p < 0.001$). These results converge to suggest that the interventions and learning contexts examined in these studies strengthen learners' evaluative and analytical thinking skills that are foundational to metacognitive regulation.

Additionally, [37] reported that self-efficacy was significantly predicted within their model, with $R^2 = 0.489$, indicating that nearly half of the variance in self-efficacy can be explained by the examined factors. Given that self-efficacy is closely related to self-regulation, this result reinforces the overall trend observed across studies.

3.1.4.2. Academic Performance Improvements

Table 6. System performance and impact on learning

Study	Context	Performance Measured	Result	Significance
[25] Satunggale Kurniawan et al., 2025	Adaptive learning media	Post-test scores	23.5% increase	Significant
[26] Annas Prasetio et al., 2025	AI chatbot intervention	Academic scores	15.7% increase	$p < 0.05$
[38] Masti Yanto et al., 2025	AI personalization	Learning outcomes	15% increase	Significant

Study	Context	Performance Measured	Result	Significance
[27] Yohana Loisa Buton et al., 2025	GPT AI in mathematics	Average scores	65 → 91.25 (40.38% increase)	Significant
[39] Faizal Amir et al., 2024	AI-assisted advance organizer	Post-test scores	Exp: 60.72, Ctrl: 45.65; N-Gain: 0.599 vs 0.036	–
[40] Muchtar et al., 2025	AI learning platform	Academic grades	70 → 80	$p < 0.05$
[41] Marsithah et al., 2024	AI-based learning	Academic performance	45% increase per usage increment; Regression = 0.45	Significant
[42] Muttaqin Kholis Ali et al., 2025	AI-based media	Conceptual understanding	15–25% increase	Significant

A consistent body of evidence from recent studies demonstrates that AI-driven learning interventions substantially improve students' academic performance across diverse educational contexts. [25] reported a 23.5% increase in post-test scores through adaptive learning media, indicating that personalized content presentation can meaningfully enhance mastery of learning materials. Similarly, [26] found that an AI chatbot intervention improved academic scores by 15.7%, with statistical significance ($p < 0.05$), suggesting that interactive AI feedback strengthens understanding and knowledge retention.

The positive impact of personalization is further supported by [38], who observed a 15% increase in learning outcomes through AI-based personalization, reinforcing the role of adaptive pathways in optimizing student learning. A more substantial improvement was reported by Loisa [27], whose implementation of GPT-based AI in mathematics instruction led to an increase in average scores from 65 to 91.25, representing a 40.38% improvement with significant results. This finding highlights the transformative potential of AI-generated explanations and problem-solving assistance in complex subject areas.

Experimental evidence further amplifies these trends. [39] demonstrated that AI-assisted advance organizers produced superior post-test performance in the experimental group (60.72) compared to 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 enhance students' conceptual acquisition.

Additional enhancements in academic grades were reported by [40], where the use of an AI learning platform resulted in score improvements from 70 to 80 ($p < 0.05$). In alignment with these findings, [41] identified that AI-based learning increased academic performance by 45% per usage increment, corroborated by a regression coefficient of 0.45, reflecting a strong linear relationship between AI usage and academic achievement.

Finally, [42] documented increases of 15–25% in conceptual understanding through AI-based media, confirming that AI tools effectively support higher-order comprehension and structured knowledge building.

3.1.4.3. Motivation and Engagement Effects

Table 7. Key factors/variables that are often reported

Author & Year	Variable / Focus	Result / Key Finding
[38] Yanto et al., 2025	Learning motivation	20% increase
[40] Muchtar et al., 2025	Motivation with AI platforms	84% of students reported increased motivation
[41] Iis Marsithah et al., 2024	Student engagement	68% increase in participation
[43] Suryawijaya et al., 2025	Learning motivation	75% reported positive impact
[44] Syamsidar Hs et al., 2024	Confidence in task completion	38% strongly agree, 34% agree

Findings from recent studies consistently demonstrate that AI-supported learning environments have a substantial positive impact on student motivation and engagement. [38] reported a 20% increase in learning motivation, showing that AI-based personalization can effectively stimulate students' interest and persistence in the learning process. This motivational enhancement is echoed in the work of [40], where 84% of students reported increased motivation when engaging with AI learning platforms, indicating that inteactive AI features foster a more supportive and engaging learning atmosphere.

The influence of AI tools extends beyond motivation to significantly improve student engagement. [41] documented a 68% increase in student participation, suggesting that AI-based learning environments successfully encourage active involvement and reduce passive learning behaviors. Such improvements in engagement reflect the capacity of AI systems to provide timely feedback, adaptive challenges, and personalized learning pathways.

Learners' perceptions further reinforce these outcomes. [43] found that 75% of students reported a positive impact on their learning motivation, highlighting the widespread acceptance and psychological benefits of AI-enhanced instruction. In addition, [44] reported strong levels of confidence among students during task completion, with 38% strongly agreeing and 34% agreeing that AI-supported approaches improved their confidence. This indicates that AI contributes not only to motivational gains but also to the development of learners' self-belief and task readiness.

3.1.5. Self-Regulation and Metacognitive Skill Development

The integration of AI technologies has shown a considerable impact on the development of students' self-regulation, extending across cognitive, affective, and behavioral dimensions. Through automatic feedback and personalized recommendations, AI has enhanced learners' self-awareness regarding their progress and performance [31]. This awareness encouraged students to reflect more deeply on their learning processes and outcomes, creating a foundation for improved self-regulatory behavior.

In addition to awareness, the presence of AI-assisted environments strengthened students' ability to set realistic goals and select effective learning strategies suited to their needs [19]. The technology provided continuous scaffolding that supported adaptive decision-making, allowing students to take greater ownership of their learning pathways. Real-time formative assessments embedded within AI systems further cultivated self-monitoring and self-assessment skills, ensuring that students could identify gaps and make timely adjustments in their learning [45].

Several studies highlighted increased autonomy and independence as major outcomes of AI integration in learning [30]. The decreasing reliance on direct human guidance reflected a shift toward more self-directed learning behaviors, where students demonstrated confidence and initiative in managing their own progress. In music education, for example, the FERMATA AI system played a crucial role in developing personal awareness helping students understand their musical identity and structure professional growth strategies more effectively [22].

Beyond the domain of self-regulation, AI integration also contributed substantially to metacognitive skill development, particularly in fostering critical thinking. Among educational technology students, AI-assisted systems accounted for 53.2% of observed improvements in critical thinking [36]. Similarly, AI-based learning media exhibited large effect sizes ($\eta^2 = 0.95$) in enhancing critical thinking within civic education contexts [35]. These findings suggest that AI not only supports the regulation of one's own learning but also promotes higher-order cognitive processes necessary for reflective and analytical thinking.

3.1.6. Digital Learning Environment Characteristics

Table 8. Level of metacognitive support in the system

Komponen	Deskripsi	Tingkat

Platform Type	Web-based systems [19], LMS-embedded [29], Mobile apps [21]	High
Learning Modality	Blended learning [34], Fully online [46], Face-to-face with digital tools [23]	Mixed
Personalization Features	Adaptive content delivery [25], Learning path customization [47], Preference mapping [45]	High
Real-time Feedback	Automatic performance feedback [45], Grammar and style [23], Chatbot responses [26].	High
Collaborative Features	Teacher dashboard analytics [23], Discussion forums [29], Peer interaction platforms [47].	Moderate

The digital learning system developed across various studies demonstrates the integration of several key components that play a significant role in enhancing the effectiveness and flexibility of the learning process. Each component possesses distinct characteristics and varying levels of implementation, collectively reflecting the evolving direction of modern educational technology.

In terms of the Platform Type, the implementation level is categorized as High, indicating that platform design serves as the foundation of digital learning system development. Multiple forms of platforms are utilized, including web-based systems [19], LMS-embedded platforms [29], and mobile applications [21]. This diversity provides flexible access for learners across devices and learning contexts, both formal and informal. Such flexibility reflects an intentional effort to expand learning accessibility while maintaining user convenience.

The next component, Learning Modality, shows a Mixed level of implementation, reflecting the diversity of approaches in adopting educational technology. Previous research identifies several models frequently applied, such as blended learning, which combines online and face-to-face sessions [34], fully online learning conducted entirely through digital platforms [46], and face-to-face learning enhanced by digital tools [23]. This variety demonstrates that educational institutions continue to adapt their pedagogical strategies to learners' needs and technological readiness.

Following that, the Personalization Features component obtains a High level due to its major contribution to enhancing individualized learning experiences. The systems developed are capable of tailoring content based on learners' abilities and preferences through adaptive content delivery [45], providing flexibility in designing personalized learning pathways through learning path customization [47], and recognizing learning styles and preferences via preference mapping [45]. Through these personalization mechanisms, learning becomes more relevant, efficient, and learner-centered, aligning with the principles of adaptive and individualized education.

Equally important, Real-time Feedback also demonstrates a High level of implementation. This component plays a crucial role in ensuring that learners receive immediate and meaningful feedback throughout the learning process. Features such as automatic performance feedback [45], grammar and style correction [23], and chatbot-based interactions [26] illustrate the capability of technology to deliver fast and accurate learning support. By providing real-time responses, these systems help learners correct mistakes promptly and reinforce their understanding effectively.

Meanwhile, Collaborative Features are categorized at a Moderate level, suggesting that digital collaboration is still under development but shows significant potential. Such features include teacher dashboard analytics for monitoring student progress [23], discussion forums as spaces for interaction and reflection [29], and peer interaction platforms that foster cooperative and community-based learning [47]. Although not as intensively adopted as other components, collaborative tools are becoming essential in reinforcing the social dimension of digital learning environments.

Overall, current digital learning systems demonstrate strong development in components with high implementation levels, such as flexible platforms, adaptive personalization features, and effective real-time feedback mechanisms. However, collaborative aspects still require further enhancement to support a more interactive and participatory learning environment. The balanced integration of these components forms the foundation for an effective, adaptive, and sustainable digital learning ecosystem.

3.1.7. Implementation Challenges

Table 9. Categories of findings and distribution of studies

Category	Description	Studies Reporting
Technical	Infrastructure limitations, integration complexity, accuracy concerns	[31]
Pedagogical	Teacher training needs, curriculum alignment, over-automation risks	[48]
Ethical	Privacy concerns, plagiarism risks, transparency issues	[47]
Student-Related	Dependency risks, reduced creativity, adaptation difficulties	[44]
Institutional	Policy gaps, resource constraints, systemic barriers	[49]

Table-based synthesis of implementation barriers shows that challenges cluster into five main categories: technical, pedagogical, ethical, student-related, and institutional, each highlighted across multiple studies [13,32,3]. This categorization indicates that AI integration issues in education are not merely technological, but also embedded in teaching practices, learner characteristics, and systemic conditions [13,32]. Such a multi-dimensional pattern reinforces the need to view AI implementation as an ecosystem-level change rather than a purely technical upgrade [47].

3.2. Discussion

3.2.1. Technical and Infrastructure Challenges

Technical challenges emerged as significant barriers to AI implementation across the reviewed studies. Infrastructure limitations, including limited internet access and inadequate technological facilities, constrained the effective adoption of AI-supported learning systems in several contexts [31]. Integration complexity between AI tools and existing educational platforms, such as learning management systems or legacy institutional systems, posed ongoing technical and maintenance challenges for practitioners and institutions [21]. In addition, accuracy and reliability concerns regarding AI-generated outputs required educators and students to implement verification processes, reducing the extent to which AI tools could be fully trusted and seamlessly integrated into high-stakes learning activities [43].

3.2.2. Pedagogical Challenges

Beyond technical issues, pedagogical challenges played a central role in shaping the success of AI implementation. Teacher readiness consistently emerged as a critical factor, with educators requiring substantial training to plan, operate, and interpret AI-based and adaptive learning systems effectively [48]. Difficulties in aligning AI tools with existing curricula and learning objectives further complicated integration, as some applications were not designed with specific competency standards or assessment frameworks in mind [22]. Moreover, several studies raised concerns that excessive automation of learning activities might undermine intrinsic motivation and reduce opportunities for meaningful human interaction, thereby challenging the intended role of AI as a complement rather than a replacement for teacher-led instruction [47].

3.2.3. Ethical Concerns

Ethical considerations surrounding AI use in education encompassed multiple interrelated dimensions. Privacy and data security issues related to the collection, storage, and analysis of student information required careful governance to prevent misuse and ensure compliance with institutional and regulatory expectations [47]. Risks of plagiarism and academic integrity violations emerged when AI tools were used to generate or heavily assist in producing assignments, creating challenges for fair assessment and authentic demonstration of learning [19]. In parallel, potential dependency on AI tools raised pedagogical concerns, as over-reliance on automated support was perceived as potentially diminishing students' opportunities to exercise critical thinking and creativity in independently constructing ideas [44].

3.2.4. Interpreting Heterogeneous Findings

3.2.4.1. Explaining Variation in Effect Sizes

The substantial variation in reported effect sizes across studies, ranging from modest coefficients (for example $\beta = 0.267$) to very large effects (such as $\eta^2 = 0.95$), can be attributed to contextual and methodological differences rather than to fundamental disagreement about the educational efficacy of AI. This pattern indicates that how AI is implemented and in what setting it is used plays a critical role in determining the magnitude of its impact.

3.2.4.2. Context and Population Distinctions

Studies reporting the largest effects generally employed domain-specific AI implementations embedded within structured pedagogical frameworks. For instance, the critical thinking intervention that achieved $\eta^2 = 0.95$ combined AI-based media with a quasi-experimental design in civic education [35], while the mathematics intervention showing a 40.38% improvement used GPT-based AI within a controlled small-group setting [27]. In contrast, studies that examined more general AI use without systematic instructional integration reported comparatively modest effects, such as $\beta = 0.333$ for learning independence [19]. Taken together, these findings suggest that AI effectiveness is highly contingent upon purposeful pedagogical design rather than mere technological adoption.

3.2.4.3. Study Quality Hierarchy

A clear hierarchy of study designs also helps explain differences in observed effect sizes. Among the quantitative studies, quasi-experimental designs with control groups consistently produced more robust evidence than correlational surveys. Experimental studies by [34], [39], and [35] demonstrated substantial and statistically significant improvements, whereas survey-based studies relying on self-reported AI use typically yielded smaller effect sizes. This pattern implies that controlled, researcher-designed AI interventions tend to generate stronger and more reliable effects than naturalistic usage patterns that are not tightly guided by pedagogical structures.

3.2.4.4. Mechanistic Explanations

Divergent findings regarding self-regulation can be further clarified by examining the mechanisms through which AI engages metacognitive processes. Studies that reported strong self-regulation outcomes generally employed AI systems that provided structured scaffolding and reflective feedback to support learners' monitoring and regulation of their own learning [22]. By contrast, studies that raised concerns about dependency often involved less structured AI use oriented toward task completion, where students could rely on AI to do the work rather than to support reflection and strategy use [50]. Thus, the key distinction is not whether AI affects self-regulation, but whether the implementation design supports or supplants metacognitive engagement.

3.2.4.5. Dose-Response Patterns

The relationship between AI usage intensity and learning outcomes appears to be non-linear. In one study, students who used AI tools at least three times per week reported a 75% improvement in academic performance, while regression analysis indicated a 45% increase in academic performance for each increment in AI usage [41]. However, several studies simultaneously cautioned that excessive reliance on AI can reduce critical thinking capacity and may foster over-dependence [43]. These converging results point to the existence of an optimal usage threshold, beyond which additional AI engagement may yield diminishing or even negative returns, particularly for metacognitive development.

3.2.5. Contextual Applicability of Findings

In higher education (n = 24 studies), AI integration consistently enhanced learning independence and academic performance when aligned with expectations of self-directed learning. The reported R^2 values of 0.792 for self-development [18] and 0.489 for self-efficacy [37] indicate substantial explanatory power in university contexts characterized by high learner autonomy. In secondary education (n = 13 studies), the strongest effects were observed when AI was implemented within teacher-guided and scaffolded frameworks; for example, a 23.5% post-test improvement with adaptive learning media [45] and significant gains in critical thinking [35] were both achieved in carefully controlled pedagogical environments. In primary education (n = 3 studies), the evidence base remains limited but promising, with AI literacy interventions showing substantial reductions in technical difficulties (from 46% to 16%) and marked increases in ethical awareness (from 43% to 87%) across iterative implementation cycles [51].

3.2.6. Reconciling Positive Effects and Implementation Concerns

The apparent tension between consistently positive learning outcomes and substantial implementation challenges reflects a distinction between efficacy under controlled conditions and effectiveness in naturalistic deployment. Studies reporting strong effects typically involved researcher-led interventions implemented in settings with adequate infrastructure and explicit teacher support, enabling AI tools to be tightly aligned with instructional design and learning goals [34]. By contrast, many implementation challenges were documented in survey-based studies that examined broader institutional adoption, where variability in infrastructure, policy support, and teacher readiness was much greater [48].

This pattern suggests that the learning analytics capabilities of AI to enhance self-regulation and related outcomes are empirically well established, but their successful translation into everyday practice depends on a range of enabling conditions. In particular, infrastructure readiness remains a prerequisite for reliable deployment [31], while teacher digital literacy is essential for making informed pedagogical use of AI tools rather than treating them as purely technical add-ons [42]. At the same time, robust ethical frameworks are required to govern issues such as data use, transparency, and academic integrity in AI-supported learning environments [47]. The finding that 91.1% of the variance in learning independence is not explained by AI use alone [19] further underscores that AI should be understood as one element within a broader ecosystem of motivational, environmental, and pedagogical factors, rather than as a standalone determinant of learning success.

3.2.7. Future Implications

The reviewed literature converges on several key recommendations for advancing AI-enabled learning analytics and self-regulation support in educational settings. These recommendations span policy, pedagogy, research, and scalability considerations, reflecting the need for a coordinated and multi-level approach to AI integration.

3.2.8. Policy and Institutional Support

Institutional policies that support AI integration need to be developed in parallel with investments in digital infrastructure to ensure that technological capabilities are matched by clear governance frameworks [48]. Comprehensive teacher training programmes that address both technical competencies and pedagogical integration strategies are essential so that educators can meaningfully embed AI tools into teaching and assessment practices rather than using them superficially [34]. In addition, clear ethical guidelines governing data privacy, algorithmic transparency, and academic integrity must accompany AI deployment to safeguard learners' rights and maintain trust in AI-supported educational environments [47].

3.2.9. Pedagogical Design Principles

From a pedagogical perspective, AI should be designed to augment rather than replace teacher–student interaction, with systems that deliberately balance personalization with opportunities for social and collaborative learning [47], [49]. Implementation strategies are encouraged to prioritize metacognitive scaffolding such as prompts for reflection, planning, and self-monitoring rather than mere task automation, thereby fostering student agency while reducing the risk of over-dependence on AI-generated solutions [23], [43].

3.2.10. Synthesis Aligned to Research Questions

The systematic review findings directly address the three research questions outlined in the introduction. RQ1 (mapping AI-driven learning analytics tools) reveals that predictive analytics dominate (44%, n=15 studies) for performance/adaptability prediction, followed by adaptive dashboards (32%, n=11) providing real-time behavioral recommendations, and generative AI assistants (24%, n=8) delivering NLP-based scaffolding prompts, with LMS integration as the strongest platform.

RQ2 (synthesizing effects) demonstrates strong evidence from high-quality studies (n=21, ≥80% MMAT): consistent improvements in self-regulated learning (β=0.267-0.639), metacognitive development (η^2=0.95 critical thinking), academic performance (15-40% gains), and motivation (20-84% reported increases), with largest effects from quasi-experimental designs combining AI tools with structured pedagogy.

RQ3 (mechanisms and challenges) identifies feedback loops and scaffolding as primary pathways linking AI tools to SRL phases (forethought→performance→reflection), moderated by teacher training, infrastructure readiness, and study quality, while implementation barriers cluster across technical (infrastructure), pedagogical (training gaps), and ethical dimensions (privacy/dependency) that explain heterogeneous findings across contexts.

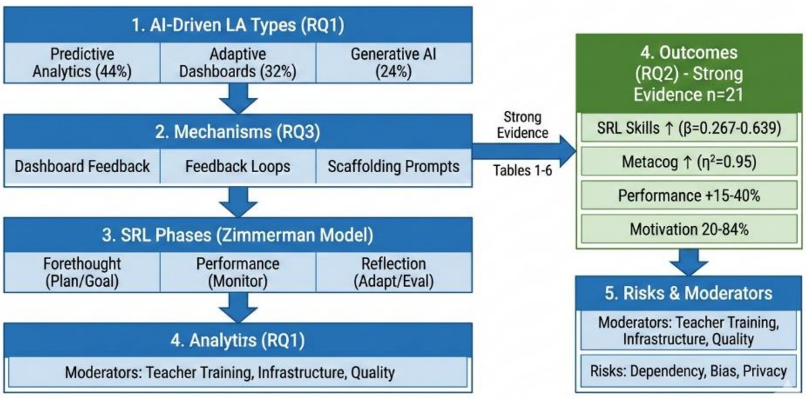

Figure 2. SRL Conceptual Framework

Model integrates RQ1-3 showing AI-LA types → mechanisms → Zimmerman SRL phases → outcomes (strong evidence n=21), moderated by teacher readiness/infrastructure, with identified risks. Evidence strength: strong core pathways, medium moderators/risks.

3.2.11. Research Directions

The literature also highlights several directions for advancing the empirical evidence base. Future studies are urged to employ larger and more diverse samples to improve the generalizability of findings across institutions, disciplines, and learner profiles [39]. Longitudinal research designs are needed to examine the long-term impacts of AI on cognitive, behavioural, and social-emotional development, moving beyond short-term post-test gains [52]. Furthermore, systematic investigation of mediator variables such as motivation, engagement, and individual differences would deepen mechanistic understanding of how and for whom AI-supported interventions are most effective [27].

3.2.12. Scalability Considerations

Finally, the reviewed studies point to important considerations for scaling AI initiatives beyond pilot contexts. Gradual curriculum integration accompanied by sustained stakeholder training covering teachers, students, and administrators emerges as a preferred strategy to support sustainable adoption [42]. Collaboration among governments, educational institutions, and technology companies is viewed as necessary to align policy, practice, and technological innovation in ways that are educationally meaningful and context sensitive [32]. Financial support mechanisms that ensure equitable access to AI tools and infrastructure remain critical to prevent the widening of existing educational inequalities as AI adoption expands [38].

4. Conclusion

This systematic literature review synthesizes evidence from 34 empirical studies and reviews examining how AI-driven learning analytics affect self-regulated learning (SRL), metacognitive development, and academic achievement in primary, secondary, and higher education. Following the PRISMA 2020 guidelines, studies were identified from Scopus, Web of Science, ERIC, and Google Scholar (2020-2025) with the following inclusion criteria: AI-LA intervention, standardized SRL/metacognition measures, and pre-post/comparative empirical data. Findings indicate that predictive analytics (44%), adaptive dashboards (32%), and generative AI (24%) consistently support key SRL processes (monitoring, strategy, goal setting) and enhance motivation, engagement, and academic performance (15-40% gain, β=0.267-0.639, η^2=0.95) in high-quality studies (n=21, MMAT≥80%). However, significant implementation challenges include infrastructure constraints, teacher readiness, data privacy, and the risk of dependency that can weaken critical/metacognitive thinking. This review confirms that AI-driven learning analytics has strong potential to strengthen SRL if integrated within a structured pedagogical framework and supported by institutional policies that position AI as scaffolding for learning agency, not a substitute for human judgment.

References

[1] C. C. Lin, A. Y. Q. Huang, and O. H. T. Lu, "Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review," Smart Learn. Environ., vol. 10, no. 1, 2023, doi: 10.1186/s40561-023-00260-y.
[2] M. Gordon et al., "A scoping review of artificial intelligence in medical education: BEME Guide No. 84," Med. Teach., vol. 46, no. 4, pp. 446–470, 2024, doi: 10.1080/0142159X.2024.2314198.
[3] E. Araka, E. Maina, R. Gitonga, and R. Oboko, "Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018)," Res. Pract. Technol. Enhanc. Learn., vol. 15, no. 1, 2020, doi: 10.1186/s41039-020-00129-5.
[4] C. Deneen, "Technology and self-regulated learning," Pacific J. Technol. Enhanc. Learn., vol. 7, no. 2, p. 27, 2025, doi: 10.24135/pjtel.v7i2.230.
[5] Sri Umi Lestari, Syarifuddin, and Nurhasan, "Komik Digital Berbasis Articial Intelegence Untuk Pendidikan Agama Islam di Sekolah Menengah Pertama: Analisis Kebutuhan," Didakt. J. Kependidikan, vol. 14, no. 3, pp. 4263–4272, 2025, doi: 10.58230/27454312.2893.
[6] Y. Xue, F. B. Khalid, and A. B. A. Karim, "Emerging Trends in Self-Regulated Learning: A Bibliometric Analysis of MOOCs and AI-Enhanced Online Learning (2014–2024)," Int. J. Learn. Teach. Educ. Res., vol. 24, no. 1, pp. 420–442, 2025, doi: 10.26803/ijlter.24.1.21.
[7] M. Lan and X. Zhou, "A qualitative systematic review on AI empowered self-regulated learning in higher

education," npj Sci. Learn., vol. 10, no. 1, 2025, doi: 10.1038/s41539-025-00319-0.
[8] R. Guan, M. Raković, G. Chen, and D. Gašević, "How educational chatbots support self-regulated learning? A systematic review of the literature," Educ. Inf. Technol., vol. 30, no. 4, pp. 4493–4518, 2025, doi: 10.1007/s10639-024-12881-y.
[9] A. Mohebbi, "Enabling learner independence and self-regulation in language education using AI tools: a systematic review," Cogent Educ., vol. 12, no. 1, 2025, doi: 10.1080/2331186X.2024.2433814.
[10] A. Goyal, "AI as a Cognitive Partner: A Systematic Review of the Influence of AI on Metacognition and Self-Reflection in Critical Thinking," Int. J. Innov. Sci. Res. Technol., pp. 1231–1238, 2025, doi: 10.38124/ijisrt/25mar1427.
[11] J. Sardi et al., "How Generative AI Influences Students' Self-Regulated Learning and Critical Thinking Skills? A Systematic Review," Int. J. Eng. Pedagog., vol. 15, no. 1, pp. 94–108, 2025, doi: 10.3991/ijep.v15i1.53379.
[12] H. Juan and R. Nagappan, "A Comprehensive Literature Review on AI-Enhanced Autonomous Learning Mechanisms in Vocational Education," Malaysian J. Soc. Sci. Humanit., vol. 10, no. 3, p. e002958, 2025, doi: 10.47405/mjssh.v10i3.2958.
[13] S. Chardonnens, "Adapting educational practices for Generation Z: integrating metacognitive strategies and artificial intelligence," Front. Educ., vol. 10, 2025, doi: 10.3389/feduc.2025.1504726.
[14] E. Hussein, M. Hussein, and M. Al-Hendawi, "Investigation into the Applications of Artificial Intelligence (AI) in Special Education: A Literature Review," Soc. Sci., vol. 14, no. 5, 2025, doi: 10.3390/socsci14050288.
[15] J. M. Aguado-García, S. Alonso-Muñoz, and C. De-Pablos-Heredero, "Using Artificial Intelligence for Higher Education: An Overview and Future Research Avenues," SAGE Open, vol. 15, no. 2, pp. 1–22, 2025, doi: 10.1177/21582440251340352.
[16] Dinesh Deckker and Subhashini Sumanasekara, "Systematic Review on Ai in Emotional Intelligence and Psychological Education," EPRA Int. J. Res. Dev., pp. 400–414, 2025, doi: 10.36713/epra21351.
[17] Q. Xia, X. Weng, F. Ouyang, T. J. Lin, and T. K. F. Chiu, "A scoping review on how generative artificial intelligence transforms assessment in higher education," Int. J. Educ. Technol. High. Educ., vol. 21, no. 1, 2024, doi: 10.1186/s41239-024-00468-z.
[18] S. A. Rasid and M. F. Al Azhari, "The influence of personality traits of AI user students on increasing self-development in learning: PLS-SEM analysis," Abjadia Int. J. Educ., vol. 10, no. 2, pp. 306–317, 2025, doi: 10.18860/abj.v10i2.32579.
[19] N. Ardana, H. Indrawati, and F. Trisnawati, "Pengaruh Pemanfaatan Teknologi Artificial Intelligence terhadap Kemandirian Belajar (Studi pada Mahasiswa Jurusan Pendidikan IPS Universitas Riau)," JIIP - J. Ilm. Ilmu Pendidik., vol. 8, no. 8, pp. 9688–9699, 2025, doi: 10.54371/jiip.v8i8.8758.
[20] S. Arti and E. Suherlan, "Evaluasi Kinerja Machine Learning dalam Memprediksi Kemampuan Adaptasi Mahasiswa pada Lingkungan Pembelajaran Daring," J. Pustaka AI (Pusat Akses Kaji. Teknol. Artif. Intell., vol. 5, no. 1, pp. 50–57, 2025, doi: 10.55382/jurnalpustakaai.v5i1.901.
[21] C. R. I. Permatasari and T. N. H. Yunianta, "E-Learning Artificial Intelligence Sebagai Suplemen Dalam Proses Metacognitive Scaffolding Pemecahan Masalah Integral," AKSIOMA J. Progr. Stud. Pendidik. Mat., vol. 10, no. 2, p. 829, 2021, doi: 10.24127/ajpm.v10i2.3490.
[22] E. J. Jaohari, Z. S. Soeteja, and M. Y. Ramadhan, "Penerapan FERMATA AI dalam Pendidikan Musik untuk Meningkatkan Personal Awareness Mahasiswa Musik," J. Kiprah Pendidik., vol. 4, no. 3, pp. 320–334, 2025, doi: 10.33578/kpd.v4i3.p320-334.
[23] R. Sianipar, "Integrasi Ai Dalam Pembelajaran Teks Naratif: Studi Tentang Proses, Hasil, Dan Persepsi," Al-Irsyad J. Educ. Sci., vol. 4, no. 2, pp. 251–264, 2025, doi: 10.58917/aijes.v4i2.226.
[24] L. Lena, R. Leandros, and D. F. Murad, "Akurasi Prediksi Nilai Mahasiswa menggunakan Informasi Kontekstual pada Personalisasi Sistem Rekomendasi," J. Tek. Inform. Unis, vol. 9, no. 1, pp. 55–60, 2021, doi: 10.33592/jutis.v9i1.1285.
[25] S. Kurniawan, M. A. Rahman, and Y. Sugiarno, "Pengembangan Media Pembelajaran Adaptif Menggunakan Pemrograman Berbasis AI dan Psikologi Pendidikan di SMPN 2 Candi," J. Inf. Syst. Educ. Dev., vol. 3, no. 2, pp. 5–11, 2025, doi: 10.62386/jised.v3i2.131.
[26] A. Prasetio, Y. Utami, and S. Handayani, "Penerapan Artificial Intelligence untuk Siswa/i SMK Swasta Mustafa Perbaungan," J. Has. Pengabdi. Masy., vol. 4, no. 1, pp. 38–43, 2025, doi: 10.62712/juribmas.v4i1.359.
[27] Y. L. Buton, B. F. Liarian, R. A. Teti, M. F. Dhato, and F. M. Sewo, "Penerapan Pembelajaran Matematika Berbasis It Dengan Gpt Ai Sebagai Alat Bantu," Al-Irsyad J. Math. Educ., vol. 4, no. 2, pp. 307–316, 2025, doi: 10.58917/ijme.v4i2.256.
[28] S. Sumarlin and D. Anggraini, "Data Mining Pendidikan: Prediksi Gaya Belajar Mahasiswa Teknik Menggunakan Machine Learning," J. Teknol. Inf. dan Ilmu Komput., vol. 12, no. 3, pp. 563–572, 2025, doi: 10.25126/jtiik.2025129190.
[29] M. F. Ibrahim, "Model Rangkaian Neural Bagi Penentuan Gaya Pembelajaran Pelajar Berasaskan Model Felder-Silverman," Asean J. Teach. Learn. High. Educ., vol. 14, no. 2, pp. 108–121, 2022, doi: 10.17576/ajtlhe.1402.2022.08.
[30] B. P. Gautama, N. Indriana Agusti, D. Lazuardi, and C. Maman Fathurohman, "Artificial Intelligence (Ai)

and Chatgpt in Learning: Assessing Effectiveness and Overcoming Challenges in the Age of Industry 4.0," J. Apar., vol. 8, no. 1, pp. 52–68, 2024, doi: 10.52596/ja.v8i1.243.

[31] L. K. Dewi and N. I. Lahizha, "Integrasi Artificial Intelligence (AI) dalam Sistem Pembelajaran Adaptif untuk Meningkatkan Belajar Mandiri Mahasiswa," JIIP - J. Ilm. Ilmu Pendidik., vol. 8, no. 9, pp. 10916–10921, 2025, doi: 10.54371/jiip.v8i9.9327.

[32] L. Parn, T. Mariyanti, and A. Widyakto, "Optimalisasi E-Learning dengan AI Adaptif untuk Pendidikan Inklusif," J. MENTARI Manajemen, Pendidik. dan Teknol. Inf., vol. 3, no. 2, pp. 168–176, 2025, doi: 10.33050/mentari.v3i2.768.

[33] D. Yani and K. Kusrini, "Metode Machine Learning dan Deep Learning dalam Prediksi Kinerja Siswa: Tinjauan Sistematis," G-Tech J. Teknol. Terap., vol. 9, no. 1, pp. 530–539, 2025, doi: 10.70609/gtech.v9i1.6501.

[34] A. Usman and F. Faradina, "Optimalisasi Peran AI dan Learning of Thinking (LOT) dalam pembelajaran fisika untuk Meningkatkan Kemandirian Belajar Siswa," KUANTUM J. Pembelajaran dan Sains Fis., vol. 6, no. 1, pp. 54–65, 2025, doi: 10.63976/kuantum.v6i1.829.

[35] S. Supriadi, A. Zulfaidah, M. Nasir, and S. T. Dhayinta, "Pengaruh Media Pembelajaran Berbasis Kecerdasan Buatan Terhadap Keterampilan Berpikir Kritis dan Hasil Belajar PPKn Siswa di SMA," Pema, vol. 5, no. 2, pp. 684–690, 2025, doi: 10.56832/pema.v5i2.1253.

[36] G. F. Ayuningtyas, H. K. Fahranie, I. Muslimah, S. Hadiansyah, S. Elzahra, and B. Setiawan, "Pengaruh Penggunaan AI Terhadap Peningkatan Critical Thinking Mahasiswa Teknologi Pendidikan," Action Res. J. Indones., vol. 6, no. 4, 2024, doi: 10.61227/arji.v6i4.234.

[37] Y. A. Putri and N. Trisnawati, "Pengaruh Penggunaan Chat GPT , Regulasi Diri Dan Dukungan Sosial Teman Sebaya Terhadap Self Efficacy Mahasiswa Pendidikan Administrasi Perkantoran," J. Ilm. Profesi Pendidik., vol. 10, no. 4, pp. 3067–3073, 2025.

[38] M. Yanto, Mad Sa'I, and Nailatur Rizqiyah, "Personalisasi Pendidikan Berbasis AI dalam Meningkatkan Kualitas Belajar Siswa," Entita J. Pendidik. Ilmu Pengetah. Sos. dan Ilmu-Ilmu Sos., pp. 507–522, 2025, doi: 10.19105/ejpis.v1i.19116.

[39] F. Amir and A. Saddia, "Penerapan Model Pembelajaran Advance Organizer Berbantuan Artificial Intelligence (Ai) Terhadap Peningkatan Pemahaman Konsep Mahasiswa Pendidikan Fisika Universitas Sulawesi Barat," J. Teknol. Pendidik., vol. 17, no. 2, p. 89, 2024, doi: 10.24114/jtp.v17i2.64902.

[40] Azmy Ali Muchtar, Meza Fitri Dini, and Siti Khairunnisa, "Integrasi Artificial Intelligence (AI) dalam Pembelajaran Personal: Dampaknya Terhadap Motivasi dan Hasil Belajar Siswa di SMAN 1 Pare," Al-Ubudiyah J. Pendidik. dan Stud. Islam, vol. 6, no. 1, pp. 257–261, 2025, doi: 10.55623/au.v6i1.409.

[41] I. Marsithah, P. Nadila, C. Ramadani, and A. Putri, "Pengaruh Artificial Intellegincies/ Ai Terhadap Prestasi Mahasiswa UMUSLIM," J. Komputer, Inf. dan Teknol., vol. 4, no. 2, p. 9, 2024, doi: 10.53697/jkomitek.v4i2.2121.

[42] M. K. Ali, A. M. Ali, F. F. Ali, and R. I. Ali, "Peningkatan Kualitas Pembelajaran Siswa SMA Sederajat Menggunakan Media Pembelajaran Berbasis Teknologi Kecerdasan Buatan," Cognoscere J. Komun. dan Media Pendidik., 2025, doi: 10.61292/cognoscere.252.

[43] M. R. Suryawijaya, S. Praptodiyono, and S. N. A'kaasyah, "Peran Kecerdasan Buatan dalam Mengembangkan Kompetensi dan Meningkatkan Motivasi Belajar Mahasiswa," Inform. J. Ilmu Komput., vol. 21, no. 2, pp. 155–165, 2025, doi: 10.52958/iftk.v21i2.11115.

[44] S. HS and S. S, "Efektivitas Artificial Intelegence (AI) pada Pembelajaran Sains dan Agama untuk Meningkatkan Kemandirian Belajar Mahasiswa," Pros. Semin. Nas. Fak. Tarb. dan Ilmu Kegur. IAIM Sinjai, vol. 3, pp. 18–25, 2024, doi: 10.47435/sentikjar.v3i0.3135.

[45] G. Kurniawan, A. Afriano, and D. A. E. Putri, "Pengaruh Ai dan Mind Mapping terhadap Pemahaman Materi dan Motivasi Belajar Mahasiswa Pendidikan Ekonomi," JIM J. Ilm. Mhs. Pendidik. Sej., vol. 10, no. 1, pp. 123–129, 2025, doi: 10.24815/jimps.v10i1.33875.

[46] E. B. Santosa, "Implementasi Data Mining Self Regulated Learning Siswa pada Lingkungan Belajar Daring di Perguruan Tinggi," Edudikara J. Pendidik. dan Pembelajaran, vol. 5, no. 2, pp. 123–132, 2020, doi: 10.32585/edudikara.v5i2.218.

[47] A. Amanullah, "Enhancing Student Learning Motivation: An Artificial Intelligence Framework Grounded in Motivational Theory," SiRad: Pelita Wawasan, pp. 319–336, 2025, doi: 10.64728/sirad.v1i3.art11.

[48] Miftakhuddin, D. Eriawandi, and M. R. Fahmi, "Efektivitas microlearning berbasis AI dalam meningkatkan daya serap mahasiswa," J. Inf. Technol. Eng. Sci., vol. 4, no. 2, 2025, doi: 10.63494/jites.v4i2.272.

[49] Miftakhuddin, M. R. Fahmi, and D. Eriawandi, "AI-driven adaptive learning: Personalisasi dalam pembelajaran berbasis psikologi kognitif di perguruan tinggi," J. Inf. Technol. Eng. Sci., vol. 4, no. 2, 2025, doi: 10.63494/jites.v4i2.269.

[50] A. Alfa and Farhana, "Motif dan Dampak Penggunaan Chat GPT di Era Digital pada Mahasiswa," J. Rev. Pendidik. dan Pengajaran, vol. 8, pp. 6959–6968, 2025.

[51] S. C. Relmasira, "Penggunaan Learning Experience Network Analysis (LENA) dalam Evaluasi Pembelajaran Mendalam: Studi Kasus Pengembangan Literasi AI Siswa Sekolah Dasar di Indonesia," J. Pendidik. Sains dan Komput., vol. 5, no. 01, pp. 125–131, 2025, doi: 10.47709/jpsk.v5i01.5528.

[52] M. Fadhilah and K. Isma Nuriza, "Efektivitas Pembelajaran Berbasis AI dan Augmented Reality dalam Meningkatkan Literasi Digital dan Fungsi Eksekutif Otak Siswa SD: Tinjauan Literatur Sistematis," GHANCARAN J. Pendidik. Bhs. dan Sastra Indones., 2025, doi: 10.19105/ghancaran.vi.21670.