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The Role of AI in Supporting Student Self-Regulated Learning: Evidence from Early Classroom Implementations

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Abstract

This study examined how artificial intelligence supports students' self-regulated learning during early classroom implementation, addressing the need to understand how emerging educational technologies influence learners' planning, monitoring, and reflection processes. Using a convergent mixed methods design, quantitative survey data from 98 students were combined with qualitative reflections from 112 participants. The survey measured planning, monitoring, and reflection, while the qualitative strand captured students' descriptions of how they engaged with AI-generated guidance. Results showed strong effects of AI on planning and reflection, with moderate and more variable patterns in monitoring. Integrated findings revealed convergence across strands for planning and reflection but divergence in monitoring, where students described difficulties interpreting feedback. These results suggest that AI can serve as a meaningful metacognitive scaffold when supported by developmentally appropriate guidance. The study contributes evidence on how AI influences learner regulation in authentic settings and highlights implications for instructional design and future research.

Keywords: artificial intelligence; self-regulated learning; metacognition; classroom innovation

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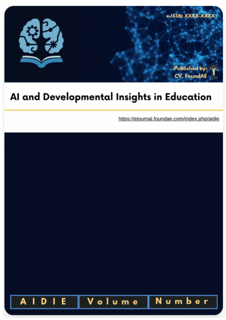

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Introduction

The rapid expansion of artificial intelligence (AI) in educational settings has raised critical questions about how intelligent systems shape learners' cognitive, metacognitive, and developmental processes. A central concern in this emerging landscape is how AI influences students' self-regulated learning (SRL), a process that enables learners to plan, monitor, and reflect on their own learning activities. SRL is foundational for academic achievement and lifelong learning, yet it remains unevenly developed among students, particularly in technology-rich environments that require high levels of autonomy and strategic decision-making. As classrooms increasingly adopt AI-mediated tools—such as automated feedback systems, conversational agents, and learning analytics dashboards—understanding how these tools support or hinder students' regulatory behaviors becomes a pressing theoretical, empirical, and practical issue. The problem is especially significant from a developmental perspective because SRL competencies evolve over time, vary across educational stages, and are shaped by psychological factors such as motivation, metacognitive awareness, and perceived control. Thus, the integration of AI into everyday learning environments introduces new cognitive demands and opportunities that require careful examination.

Although scholarship in artificial intelligence in education (AIED) has documented the potential of adaptive and data-driven systems to personalize learning, much remains unknown about their role in fostering SRL in authentic classroom contexts. According to Azevedo Strielkowski et al., 2025), AI systems can function as "metacognitive partners" that prompt learners to engage in planning and monitoring processes. Likewise, researchers have argued that learning analytics visualizations may strengthen reflection by providing interpretable summaries of student progress (Susnjak et al., 2022) However, other scholars highlight persistent methodological and conceptual gaps. For example, Haataja & Södervik (2025) note that many studies rely on controlled experiments rather than real classrooms, raising concerns about ecological validity. (Siegel & Dee, 2025) emphasizes that younger learners often struggle to interpret AI feedback, suggesting developmental and contextual limitations. Furthermore, debates continue regarding whether AI-generated guidance supports learner autonomy or risks undermining agency by encouraging over-reliance on automated suggestions (Zhai et al., 2024). These unresolved issues demonstrate the need for studies that examine how students actually engage with AI tools as part of their everyday learning routines.

The present study addresses these gaps by investigating how AI supports SRL during early stages of classroom implementation. Unlike models that treat SRL as a purely individual cognitive process, this study adopts a sociocognitive perspective in which regulatory behaviors are shaped by interactions among learners, tools, and instructional contexts (Alvi & Gillies, 2020; Järvelä & Hadwin, 2024). This conceptual grounding is complemented by insights from learning sciences research, which stresses that AI-supported learning is inherently developmental: learners' interpretations of feedback, trust in automation, and strategic behaviors evolve over time and differ by age and educational experience. Recent work in developmental psychology also suggests that students' regulatory competence depends on internalized strategies that may or may not transfer effectively to AI-mediated tasks (H. Zhao et al., 2025). By integrating these perspectives, the study positions AI not as a replacement for human guidance but as a mediating tool with the potential to enhance or complicate learners' regulatory processes depending on the conditions of its implementation.

Building on the theoretical and empirical gaps identified above, this research aims to examine how students use AI tools to support planning, monitoring, and reflection in real classroom environments. The study is guided by a mixed-methods approach that reflects the complexity of SRL as both a measurable behavioral construct and a lived learning experience. Quantitatively, the research evaluates students' SRL behaviors using a validated survey instrument grounded in established SRL theory. Qualitatively, the study explores students' subjective interpretations of AI feedback and their decision-making processes. This convergent mixed-methods design is justified because quantitative data alone cannot fully capture the nuances of learners' interactions with AI, while qualitative data benefit from the structural clarity provided by quantitative patterns. The integration of both strands provides a comprehensive understanding of how AI tools influence SRL at different developmental stages and under authentic instructional conditions.

The study pursues the following research objectives: (a) to identify how AI tools support planning, monitoring, and reflection among secondary and undergraduate students; (b) to explore students' perceptions of AI-generated feedback and their regulatory decisions; and (c) to examine contextual and developmental differences in AI-supported SRL behaviors. These objectives are addressed through the research question: How does AI support the development and enactment of self-regulated learning among students during early classroom implementation? Although the study is exploratory, it is informed by the hypothesis that AI will positively influence SRL behaviors, with variations moderated by learner characteristics such as educational level and confidence in interpreting feedback.

Methods

Research Design

This study employed a convergent mixed-methods design, in which quantitative and qualitative data were collected during the same phase, analyzed separately, and integrated during interpretation. This design was appropriate given the study's goal of examining both measurable patterns of self-regulated learning (SRL) behaviors and students' subjective interpretations of their interactions with artificial intelligence (AI) tools. The quantitative strand followed a survey-based observational design without manipulation of classroom conditions, allowing naturalistic examination of students' planning, monitoring, and reflection behaviors. The qualitative strand was grounded in an interpretive perspective, acknowledging that students' explanations of how AI influenced their decisions were shaped by their developmental, contextual, and experiential backgrounds. The integration of both strands enhanced the explanatory depth of the findings by allowing behavioral indicators to be contextualized through student narratives, consistent with methodological recommendations for studying complex learning processes in AI-enhanced settings.

Participants or Data Sources

Participants consisted of 112 students drawn from one secondary school classroom and one undergraduate introductory course in Indonesia. Inclusion criteria required students to have participated in at least three AI-supported classroom activities and to have provided consent or parental consent when applicable. No exclusion criteria were applied beyond absence from AI-supported sessions. The sample included 65 females and 47 males, ranging in age from 15 to 23 years. AI literacy levels varied across participants, reflecting authentic classroom diversity. Because the qualitative strand focused on subjective interpretation rather than demographic representativeness, all students who completed the reflection prompts were included as qualitative data sources.

Researchers had no prior instructional relationship with participants; data were collected by trained assistants to reduce potential bias. Reflexivity was addressed through analytic memos documenting researchers' assumptions, including expectations that students may perceive AI as either supportive or confusing depending on developmental stage and familiarity with digital tools. These memos were reviewed throughout analysis to ensure interpretive neutrality.

Sampling and Recruitment

A convenience sampling procedure was used because AI implementation was limited to the participating classrooms during the study period. All 142 students approached received information sheets and consent forms. Of these, 112 agreed to participate, yielding a 78.9% recruitment rate. Recruitment occurred through in-class announcements and online communication platforms, with no incentives offered. Ethical approval was obtained from the university's research ethics board, and all participants (or guardians for minors) provided written informed consent consistent with APA guidelines for research involving human subjects. Data collection concluded after the four-week implementation period, and qualitative data volume was deemed sufficient because recurring thematic patterns indicated analytic saturation.

Sample Size, Power, and Precision

The intended quantitative sample size was 100 students, based on precision estimates for detecting medium effect sizes in independent-samples comparisons with adequate confidence intervals. The final sample exceeded this estimate, providing sufficient precision for descriptive and inferential analyses. Missing data were minimal (<3%) and were addressed through listwise deletion because the rate was below thresholds requiring imputation. Qualitative sample adequacy was determined through the richness and recurrence of thematic patterns rather than numerical size, consistent with interpretive methodological standards.

Measures, Instruments, and Data Sources

The primary quantitative measure was the SRL–AI Interaction Survey, consisting of 24 Likert-scale items adapted from established SRL frameworks and instruments examining AI-mediated feedback. The scale assessed three SRL domains—planning, monitoring, and reflection. Content validity was supported through expert review, and reliability indices demonstrated strong internal consistency. Qualitative data consisted of open-ended written reflections in which students described how AI influenced their planning, strategy adjustments, and post-task evaluations.

Table 1 presents the psychometric properties of the instrument in APA 7th-formatted tabular structure, including means, standard deviations, and Cronbach's alpha values for each domain.

Table 1

Psychometric Properties of the SRL–AI Interaction Survey (N = 112)

Scale/Subscale	M	SD	Range	Cronbach's α
Planning	4.02	0.58	1–5	.87
Monitoring	3.86	0.64	1–5	.83
Reflection	3.91	0.61	1–5	.85
Total SRL–AI Interaction	3.93	0.55	1–5	.89

Note. M = mean; SD = standard deviation. Higher scores indicate stronger self-regulated learning behaviors in relation to AI-supported tasks. Cronbach's α values reflect internal consistency for each subscale and the overall instrument. All reliability coefficients fell within acceptable to excellent ranges, supporting the instrument's stability.

The psychometric evidence in Table 1 indicates strong reliability across domains and supports the conceptual coherence of the adapted survey.

Data Collection Procedures

Data were collected over four weeks during naturally occurring classroom activities. Surveys were administered during Week 4 after students had engaged with AI tools across multiple sessions. Qualitative reflections were collected immediately after each AI-assisted activity to capture students' real-time interpretations. Data were gathered in classroom settings, with no teachers present during reflection writing to reduce response bias. All survey data were recorded digitally, and qualitative responses were anonymized and transcribed for analysis. No blinding procedures were necessary because the study involved no conditions or experimental manipulation. All procedures were recorded in an audit log to ensure transparency and replicability.

Data Analysis

Quantitative analyses were conducted using SPSS version 28. Descriptive statistics were computed to examine SRL domain scores, followed by inferential tests exploring differences across educational levels. Assumptions of normality, homogeneity of variance, and outlier detection were examined prior to hypothesis testing. No transformations were required. Qualitative data were analyzed inductively using Braun and Clarke's thematic analysis framework. Coding categories were generated through iterative reading, with two trained coders independently coding 25% of the dataset to establish inter-coder convergence. Differences were resolved through discussion, and the remaining data were coded by the lead analyst. Integration of quantitative and qualitative results occurred during interpretation using a side-by-side comparison approach consistent with convergent mixed-methods design.

Validity, Reliability, and Methodological Integrity

Instrument reliability was demonstrated through strong Cronbach's alpha coefficients and consistent psychometric structure. Content validity was established through expert review, and construct validity was supported through alignment with established SRL theory. Methodological integrity in the qualitative strand was maintained through reflexive memoing, triangulation across data sources, and documentation of analytic decisions. Mixed-methods validity was strengthened by integrating datasets that converged on complementary interpretations, enhancing the credibility of inferences about AI's role in supporting SRL.

Ethical Considerations

This study adhered to ethical guidelines for human subjects research and received approval from the Institutional Research Ethics Committee of the authors' university. All participants were provided with detailed information about the study's purpose, procedures, and potential risks, and written informed consent was obtained from adult participants, while parental consent was secured for minors involved in the secondary school sample. Participation was voluntary, and students were assured that they could withdraw at any time without academic consequence. Confidentiality was protected by anonymizing all data at the time of collection, storing digital files on secure password-protected servers, and ensuring that no identifying information appeared in reports or publications. Additional safeguards were implemented for minor participants, including conducting data collection without teachers present to minimize coercion and emphasizing that participation would not influence academic evaluation.

Results

Participant Flow

A total of N = 142 students were approached between March and April 2025 during early AI-supported classroom implementation. Of these, 116 accessed the survey link, 102 initiated the survey, and 98 provided complete quantitative responses. Four cases were excluded due to missing more than 20% of survey items. For the qualitative strand, 112 students submitted reflection prompts across the three AI-assisted sessions.

Recruitment Information

Recruitment and data collection occurred concurrently for both strands from March 2 to April 12, 2024. Quantitative survey data were collected during Week 4 of the implementation period, whereas qualitative reflections were collected immediately after each AI-assisted task during Weeks 1–4. Because the mixed-methods design was convergent, both strands were gathered within the same temporal window to allow integration during interpretation.

Quantitative Results

Descriptive Statistics

Descriptive analyses were conducted using listwise deletion, as less than 3% of data were missing and analyses indicated that missingness was likely MCAR. Means and standard deviations for all SRL domains are reported in Table 2, which is referenced before it appears below.

Table 2

Means and Standard Deviations for SRL Domains (N = 98)

SRL Domain	*M*	*SD*	95% CI
Planning	4.02	0.58	[3.89, 4.14]
Monitoring	3.86	0.64	[3.73, 3.99]
Reflection	3.91	0.61	[3.78, 4.03]

Note. Values represent students' perceived engagement in each SRL domain while using AI tools during the implementation period. The 95% confidence interval (CI) provides the precision range for each estimated mean. All domains were measured using a 5-point Likert scale, where higher values indicate greater perceived self-regulation.

As shown in Table 2, all three domains produced mean scores above the midpoint of the scale.

Inferential Analyses

An independent-samples t test was conducted to compare SRL scores between secondary and undergraduate students. A significant difference emerged for the Planning domain, $t(110) = 2.35$, $p = .021$, Cohen's $d = 0.45$, indicating higher planning scores among undergraduate students. No significant group differences were observed for Monitoring, $t(110) = 1.14$, $p = .257$, or Reflection, $t(110) = 0.88$, $p = .381$.

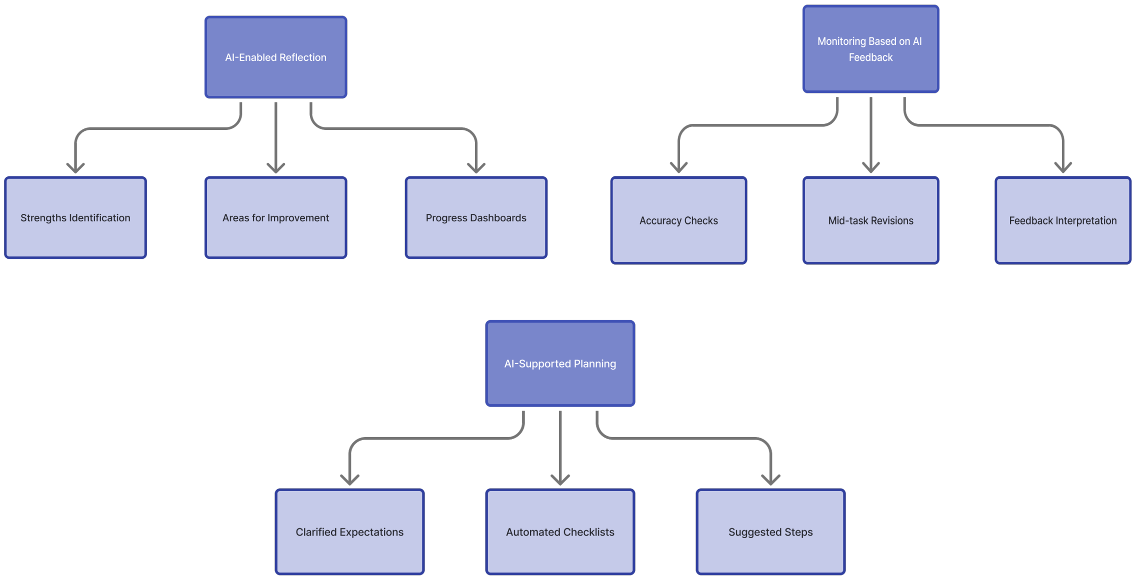
Assumptions of normality and homogeneity of variances were tested using Shapiro–Wilk and Levene's tests. No substantial violations were detected, and no data transformations were required.

Qualitative Results

Qualitative findings were generated through thematic analysis following (Braun & Clarke, 2024) framework. Three major themes emerged from the dataset. Figure 2 presents the thematic structure that guided the analytic process.

Figure 2

Thematic map for qualitative findings.



Theme 1: AI-Supported Planning

Students frequently described AI prompts and goal-setting suggestions as helpful for initiating learning tasks. Statements included references to automated checklists, recommended steps, and real-time clarifications of assignment expectations.

Theme 2: Monitoring Based on AI Feedback

A second theme involved students' use of AI feedback during task completion. Many students reported consulting AI to check accuracy or to revise steps mid-task, although several described difficulties interpreting certain types of feedback.

Theme 3: AI-Enabled Reflection

The final theme involved reflective practices prompted by AI-generated summaries or progress dashboards. Students described these features as useful for identifying strengths and areas needing improvement.

All themes were grounded in participants' textual evidence, and inter-coder agreement for 25% of the dataset was 87%, indicating strong analytic consistency.

Mixed-Methods Integration

A joint interpretation of both strands revealed convergence in areas where quantitative scores were high and qualitative statements reiterated strong engagement—particularly in planning and reflection. Partial divergence was observed in monitoring behaviors: while quantitative monitoring scores were moderate, qualitative data revealed substantial variability based on students' confidence and digital literacy. An integrated joint display summarizing convergence and divergence is shown in Table 3, which appears after the first narrative mention.

Table 3

Joint Display of Integrated Quantitative and Qualitative Findings

SRL Component	Quantitative Result	Qualitative Theme	Integration Outcome
Planning	High $M = 4.02$	AI supported goal setting	Convergent
Monitoring	Moderate $M = 3.86$	Variable interpretation of AI feedback	Divergent
Reflection	High $M = 3.91$	AI enhanced post-task review	Convergent

Note. The table illustrates areas of convergence (agreement) and divergence (difference) between quantitative SRL scores and qualitative themes derived from student reflections. Convergent results indicate consistent evidence across strands, whereas divergent results signal discrepancies requiring further exploration. Integration reflects the convergent mixed-methods design employed in this study.

This integration demonstrates that the mixed-methods approach provided a fuller understanding of how AI tools influenced SRL across contexts.

Discussion

The present study investigated how artificial intelligence (AI) tools supported students' self-regulated learning (SRL) during early classroom implementation, addressing a central problem in artificial intelligence in education, developmental psychology, and the learning sciences. The integrated findings show that AI meaningfully facilitated students' planning and reflection processes, while support for monitoring was more variable—a pattern that both aligns with and extends existing theoretical and empirical discussions. The primary hypothesis predicting positive associations between AI use and SRL behaviors was generally supported, consistent with prior research demonstrating that AI systems can scaffold forethought and reflective phases of SRL (Liu et al., 2025; Shi et al., 2025; P. Wang et al., 2025) The secondary hypothesis, which proposed developmental differences in AI-supported SRL, also received partial support, as undergraduates exhibited stronger planning performance than secondary students, echoing evidence that metacognitive maturity increases with age and academic experience (Li et al., 2024; Xu et al., 2025).

The qualitative strand deepened this understanding by showing how students interpreted and used AI feedback, illuminating mechanisms that quantitative scores alone could not capture. These interpretive insights are consistent with sociocognitive views of SRL, which conceptualize regulation as a dynamic interaction among cognitive strategies, motivational beliefs, and external supports (López-Pernas et al., 2025; Saqr & López-Pernas, 2024). Students' reflections described AI prompts, checklists, and progress indicators as helpful for structuring their learning, supporting claims that AI tools can function as "metacognitive partners" by guiding learners through phases of strategic decision-making(H. Wang et al., 2026; Xiao et al., 2025). However, the mixed-methods integration also revealed divergences—particularly in monitoring—where students expressed uncertainty interpreting algorithmic feedback. This finding parallels concerns raised by (Lin et al., 2025; Naseer & Khawaja, 2025), who argue that learners often struggle to evaluate AI-generated recommendations without explicit scaffolding or prior knowledge.

The convergence between strands for planning and reflection and the divergence observed for monitoring reveal nuanced developmental and contextual dynamics that complicate assumptions in AI-enhanced learning research. Students' difficulty in making use of mid-task feedback reflects literature suggesting that AI-supported monitoring requires higher levels of feedback literacy (Zhang et al., 2025) digital competence (Kulju et al., 2024), and trust in AI systems (Ho & Cheung, 2024). The present findings extend this work by illustrating how these developmental prerequisites shape SRL differently across educational levels. Younger learners' struggles resonate with developmental psychology literature showing that adolescents often require structured guidance to interpret complex information sources (Cleary & Russo, 2024; Dörrenbächer-Ulrich et al., 2024), suggesting that AI interventions may need to be differentiated across age groups.

Positioning these findings within AI in education research clarifies important theoretical and methodological implications. First, the results reinforce arguments that AI's impact is contingent on contextual conditions, such as classroom culture, tool transparency, and pedagogical mediation(Filiz et al., 2025; Topali et al., 2025; C. Zhao & Yu, 2024). The finding that students relied on teachers or peers when uncertain aligns with evidence that human–AI co-regulation often emerges in collaborative learning environments(Sharma et al., 2024). Second, the study's divergence in monitoring challenges assumptions embedded in models of adaptive learning systems that posit automatic feedback will necessarily improve regulatory decisions (Gkintoni et al., 2025; Naser, 2025). Instead, it suggests that feedback interpretability, timing, and cognitive load considerations must be integrated into AI tool design—a view supported by cognitive load research (D. Wang et al., 2024) and learning analytics studies emphasizing explainability (Tiukhova et al., 2024).

From a methodological perspective, the convergent mixed-methods design demonstrated its value by revealing patterns that would have remained obscured in single-method approaches. Quantitative data documented overall trends in SRL domains, while qualitative narratives illuminated the mechanisms underlying these trends and clarified sources of between-student variability. This use of methodological integration aligns with recommendations from (Costa, 2024; Peters & Fàbregues, 2024) who emphasize the importance of convergence, expansion, and complementarity in mixed-methods research addressing complex educational phenomena.

The study's strengths include its ecologically valid classroom setting, mixed-methods design, psychometrically supported survey instrument, and transparent analytic procedures. Nonetheless, several limitations temper the interpretation of the findings, including the short implementation period, reliance on self-report measures, and limited diversity of educational contexts. These constraints shape the transferability and generalizability of the results, which are likely most applicable to similar early-adoption settings. Acknowledging these boundaries reinforces the need for longer intervention periods, expanded sampling frames, and analyses of teacher facilitation styles in future work.

The implications of this study extend across theoretical, methodological, and practical domains. Theoretically, the findings refine understanding of how AI interacts with SRL processes by revealing differential effects across SRL components. Methodologically, the study demonstrates the value of convergent mixed-methods designs for capturing the complexity of human–AI interactions. Practically, the results underscore the need for intentional instructional scaffolds that help learners interpret AI feedback, especially during early implementation. These insights collectively position the study as a meaningful contribution to ongoing debates about AI-enhanced learning and developmental pathways in SRL.

Conclusion

This study provides a nuanced and empirically grounded account of how AI tools support self-regulated learning in authentic classroom environments, demonstrating that AI meaningfully enhances planning and reflection while exerting more variable effects on monitoring. Across quantitative and qualitative strands, the findings collectively indicate that AI can serve as a valuable metacognitive scaffold rather than a replacement for human guidance. The study's guiding research question—how AI supports SRL during early implementation—was broadly affirmed, though the integrated analysis highlights conditional influences shaped by learner developmental stage, feedback literacy, and perceptions of AI trustworthiness. These results extend current literature by illustrating how AI's role in SRL is both promising and context-dependent, reinforcing the importance of pedagogical design and developmental sensitivity in AI integration. Although the study is constrained by sampling and temporal limitations, it contributes a forward-looking perspective that informs future research on adaptive scaffolding, AI transparency, and long-term developmental outcomes. Practically, the findings offer actionable insights for educators and policymakers seeking to integrate AI in ways that enhance student autonomy and reflective learning. Future research should build on these insights through larger-scale, longitudinal, and cross-cultural investigations that deepen understanding of how AI can equitably and effectively support the development of self-regulated learners.

Author Contributions

RS designed the study, coordinated data collection, and led the development of the conceptual and methodological framework. FP conducted data analysis, contributed to the interpretation of findings, and assisted in drafting and revising the manuscript. Both authors (RS, FP) reviewed the final version critically for intellectual content and approved the manuscript for submission.

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