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OPTIMIZATION OF UNIVERSITY LEARNING THROUGH ARTIFICIAL INTELLIGENCE: INFLUENCE OF COGNITIVE VARIABLES ON EDUCATIONAL PLATFORMS

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SUMMARY

The emergence of artificial intelligence (AI)—especially generative AI—is transforming university learning. This article synthesizes recent evidence (2021–2025) on how cognitive variables (cognitive load, metacognition, and learning self-regulation) mediate the effects of AI-based systems (intelligent tutors, chatbots, and learning analytics) on student performance and experience. A narrative review of systematic reviews, meta-analyses and experimental studies in higher education was conducted. The findings indicate moderate to large positive effects of generative AI on performance and higher-order thinking when metacognitive scaffolding is provided and instructional design is taken care of to align cognitive load (Wang & Fan, 2025; Deng et al., 2024). The use of AI-supported tutors and learning analytics improves self-regulation in planning, execution, and reflection phases, although gaps persist in the fine measurement of cognitive processes and in adaptation to diverse contexts (Heikkinen et al., 2022; Rodríguez-Ortiz et al., 2025). Cognitive instructional design guidelines (extrinsic overload reduction, metacognitive prompts, and adaptive feedback) are proposed to maximize benefits and mitigate risks.

KEYWORDS: Artificial Intelligence, Higher Education, Cognitive Load, Metacognition, Self-Regulation of Learning, Intelligent Tutors, Generative AI.

1. INTRODUCTION

In the last decade, the higher education sector has undergone an accelerated transformation driven by advanced digital technologies, among which Artificial Intelligence (AI) occupies a relevant place. This evolution has been motivated by the need to meet a greater diversity of student profiles, teaching modalities (face-to-face, hybrid, and remote), and demands of the global labor market (Crompton & Burke, 2023). The emergence of generative AI models – such as large language models (LLMs) – has introduced new scenarios in which learning environments can dynamically adapt to student progress, generate cues of personalized support, immediate feedback, and differentiated learning paths (Florez et al., cited in Castillo-Martínez et al., 2024). In fact, a recent systematic review notes that research on AI applied to higher education doubled or tripled in 2021 and 2022 compared to previous periods (Crompton & Burke, 2023).

This technological boom, however, does not come without challenges. The integration of AI into educational platforms raises questions about its actual effectiveness, as well as about the cognitive factors that would mediate the effects on deep learning and higher-order cognitive skills (Skulmowski & Xu, 2021). Specifically, variables such as cognitive load, metacognition, and learning self-regulation (SRL) emerge as key determinants of success in digital-AI environments: without adequate load management and explicit activation of metacognitive processes, even sophisticated tools can be underutilized or generate counterproductive effects (Twabu, 2025).

On the other hand, the inclusion of AI in educational platforms goes beyond the simple "use of a chatbot". Recent literature shows that AI can act as a component of intelligent tutors, predictive learning analytics, and personalized environments, which enhances learning when embedded in a coherent instructional design. A metacritical review highlights that studies concentrate on technical domains and repeat superficial interventions, leaving important gaps in the understanding of **how** technology interacts with students' cognitive and metacognitive processes (Bond et al., 2023).

In this sense, this article aims to explore the central question: **how do cognitive variables—specifically cognitive load, metacognition, and self-regulation of learning—influence the optimization of university learning using AI in educational platforms?** To this end, it reviews recent empirical evidence (2021–2025) on the application of AI in higher education, analyzes the role of cognitive processes, and offers strategic lines for the design of educational platforms with AI that maximize deep learning. This approach is crucial in a post-pandemic context in which hybrid and digital education are consolidated, and in which students must develop not only knowledge, but also self-regulation and adaptability skills (Ocen et al., 2025). Likewise, the associated risks are addressed—such as cognitive overload, technological dependence, or metacognitive shortcomings—to propose a balanced approach that promotes effective, ethical, and student-centered learning.

2. THEORETICAL FRAMEWORK

2.1. *Cognitive Load In Digital Educational Environments*

Cognitive Load Theory (CBT) is based on the premise that working memory has a limited capacity, and that instructional design should minimize **extrinsic load**, manage intrinsic load, and optimize **German** load to promote learning (Sweller et al., 1998; cited in Skulmowski & Xu, 2021). In digital contexts, this theory has been extended to consider new load factors related to interface, interactivity and immersion. For example: "Interactive learning media, immersion, realism, disfluency and emotional design ... can induce additional task-irrelevant cognitive load while still fostering learning outcomes" (Skulmowski & Xu, 2021, p. 172).

A recent analysis indicates that "the increasing flow of stimuli can make it difficult for learners to filter information and focus on what is most relevant" (Educ. Sci., 2025, p. 2). This suggests that in educational platforms with AI support (intelligent tutors, analytics, chatbots), it is not enough to mechanically apply extrinsic load reduction: the cognitive load must be **aligned** with the desired learning outcomes, which implies conscious management of digital design (Skulmowski & Xu, 2021).

Table 1: Types Of Cognitive Load And Their Implication in Digital Environments.

Load Type	Key definition	Involvement for educational AI platforms
Intrinsic	Inherent complexity of content and its interactivity	Selection of staggered tasks; adaptive according to the student's level
Extrinsic	Load induced by design, interface, or distractions	Clean interfaces, minimal unnecessary navigation, avoidance of stimulus overload
German	Dedicated load for deep processing and schematic generation	Reflection prompts, transfer tasks, metacognitive support

The most recent research indicates that digital elements that increase extrinsic load can still generate benefits if they lead to extrinsic processes. The challenge is therefore to **manage** the interactions between load types rather than simply reducing extrinsic load.

2.2. Metacognition And Self-Regulation of Learning (SRL)

Self-regulation of learning (SRL) refers to the student's autonomous control over planning, monitoring, and evaluation of their process, while metacognition is the awareness and control of one's own cognitive processes. AI-based educational platforms can enhance these variables through scaffolding, personalized feedback, and analytics (Heikkinen et al., 2022).

A recent systematic review indicates:

"What multimodal data streams and analytical methods have been used … to measure the cognitive, metacognitive, affective, and motivational processes involved in SRL?" (A J. Pacheco et al., 2025).

In addition, in university contexts with generative AI, both AI literacy and SRL were found to significantly predict students' writing performance and digital well-being (Shi, Liu, & Hu, 2025).

Table 2: Components Of SRL And Its Linkage to AI In Educational Platforms.

Component of SRL	Short Description	AI tools that support you
Planning	Goal setting, strategy, and resources	Chatbots that help define study goals, intelligent dashboards
Monitoring	Track your own behavior and progress	Learning analytics that show usage and performance patterns
Evaluation/Reflection	Evaluation of results, adjustment of the strategy	Generative feedback systems that suggest improvements

Recently, the use of AI in SRL has been mapped as "AI-SRL research", which still has important gaps in theory, methods, and practice (Educ. Technol. J., 2025).

2.3. Artificial Intelligence, Learning Analytics and Personalization

The integration of AI in educational platforms is manifested in three large families of intervention: (a) intelligent tutoring systems (ITS) and generative chatbots, (b) learning analytics (LA) and risk prediction, and (c) personalized adaptive environments. These systems promise to elevate personalization and scalable pedagogical feedback. A recent study uses AI-powered LA for the development of metacognitive and socio-emotional competencies:

"This systematic review explores how AI-powered Learning Analytics … contribute to the development of metacognitive and socioemotional competencies …" (Pacheco et al., 2025)

The relationship between AI, SRL, and motivation was also mediated by the satisfaction of psychological needs according to Self-Determination Theory (SDT): researchers found that autonomy, competence, and relationship influence AI literacy and SRL strategies (Shi et al., 2025).

In terms of design, CBT, metacognition, and AI personalization are intertwined: adaptive systems must manage cognitive load and activate metacognition so that personalization leads to true deep learning. For example: a generative chatbot can offer clues to reduce extrinsic load, but it must also provide prompts that encourage reflection (German load) and strengthen self-regulation.

2.4. Conceptual Synthesis and Interrelations

In summary, the theoretical framework is articulated around the intersection of three major dimensions: (I) cognitive load, (II) metacognition/SRL, and (III) AI/educational analytics. The conceptual figure that can guide the analysis is the following:

- AI in educational platforms **modifies instructional designs** and forms of student interaction, which affects their **cognitive load**.
- Simultaneously, to obtain real benefits in deep learning, the processes of **metacognition** and **self-regulation** must be activated, which can mediate or moderate the effects of AI.
- Learning analytics and intelligent systems allow you to personalize the experience and provide feedback, but their effectiveness depends on how the load has been managed and metacognition activated.

This approach allows hypotheses to be raised such as: *the use of an intelligent tutor based on AI improves academic performance more when students present high levels of self-regulation and when the system interface controls extrinsic load.*

3. METHODOLOGY

In this study, a **structured narrative review** approach was employed to collect, analyze, and interpret empirical evidence (2021–2025) on the influence of cognitive variables (cognitive load, metacognition, self-regulation) on AI-mediated university learning (artificial intelligence). The methodological procedure adopted is detailed below, together with the design decisions and the criteria applied.

3.1. Study Design

The design followed the following stages:

1. Definition of research questions — focused on how

cognitive variables mediate/moderate the optimization of university learning through AI.

2. Literature search and selection — systematic reviews, meta-analyses, and experimental studies in higher education were prioritized.
3. Data extraction and synthesis — key characteristics of the studies were coded: design, context, type of AI, cognitive variables considered, learning outcomes.
4. Critical analysis and reflection — methodological quality was assessed, gaps were identified, and findings were integrated into the theoretical framework. Principles of transparency and reproducibility were adopted inspired by standards for the synthesis of evidence in education, such as those described in the review of Artificial Intelligence in Education for Higher Education.

3.2. Inclusion And Exclusion Criteria

3.2.1. Inclusion Criteria

- Studies published between 2021 and 2025 (thus ensuring that the evidence reflects recent developments in AI in education).
- Focus on higher education (universities or tertiary institutions).
- Interventions or analyses with the use of AI (intelligent tutors, chatbots, learning analytics) and explicit mention of cognitive variables (load, metacognition, self-regulation) or related processes.
- Primary studies (experimental, quasi-experimental) or systematic reviews/meta-analyses.

Exclusion Criteria

- Studies focused only on basic or secondary education.
- Works without empirical thrust (for example, mere theoretical reflections without data).
- Studies prior to 2021 or outside the Spanish or English language.

Table 1: Selection Criteria.

Criterion	*Includes*	*Excludes*
Time period	2021-2025	Before 2021
Educational level	Higher/University Education	Primary or secondary
Type of study	Empirical or systematic review/meta-analysis	Opinions, editorials without data
Variables of interest	AI + cognitive variables (load, SRL, metacognition)	AI without reference to cognitive variables

3.3. Search Procedure

The search was carried out in recognized academic databases such as Scopus, Web of Science, ERIC and Education Research Complete. Keywords included combinations of: "artificial intelligence", "higher education", "intelligent tutoring system", "chatbot", "learning analytics", "cognitive load", "self-regulated learning", "metacognition", "student learning outcome". A language filter (English/Spanish) was applied and the search strategy record was kept to ensure transparency. Previous studies suggest that even in AI in education, many systematic reviews lack rigorous methodological reporting.

3.4. Data Extraction and Encoding

For each included study, the following variables were extracted: author(s), year, country/context, population (number of students, level), type of intervention with AI, cognitive variables measured, instruments used (load tests, SRL/metacognition scales), research design (experimental, quasi, correlational), main results (effects on performance, metacognition, self-regulation), and limitations reported.

Table 2: Variables Encoded In Extraction.

Coded variable	**Short Description**
Author(s) and year	Bibliographic identification
Country / context	Geographical location of the study
Population and sample	Number of students and academic level
Type of intervention AI	Chatbot, intelligent tutor, learning analytics, etc.
Cognitive variable(s)	Cognitive load, metacognition, self-regulation
Instruments used	Platform scales, tests, logs
Study design	Experimental, quasi-experimental, correlational
Main results	Quantitative, qualitative effects
Limitations	Biases, generalizability, duration, etc.

3.5. Quality And Bias Assessment

Quality criteria adapted for educational studies with AI were applied, considering aspects such as clarity in design, randomization (or quasi-experimental justification), transparency in sample selection, instrument reporting, adequate statistical analysis, and control of cognitive variables. For example, recent reviews warn of deficiencies in methodological quality in AI for higher education. We assigned quality categories ('high', 'medium', 'low') to each study, to assess the strength of the overall evidence.

3.6. Summary Of Results

The findings were organized according to three axes: (I) effects on university learning using AI; (II) mediation or moderation of cognitive variables; (III) instructional design and technology conditions that favor the best results. A qualitative approach of synthesis (narrative) was used because the heterogeneity of designs, instruments and contexts (AI, cognitive variables) prevented a formal meta-analysis with comparable reliability to clinical settings. This decision is supported by studies that point out that many reviews on AI in education still rely on qualitative methods due to the novelty of the field.

3.7. Ethical Considerations

We respected authorship and adequately reported original studies. Although there was no new data collection with human subjects, reflection was made on ethics in AI and education — in line with recent recommendations for transparency, equity, and data protection in educational AI.

4. RESULTS

The main findings derived from the recent literature review (2021–2025) on the optimization of university learning using AI are presented below, with special attention to the influence of cognitive variables (cognitive load, metacognition, self-regulation of learning —SRL—).

1. Effects Of AI On University Learning

- A study of 223 college students found that the use of generative AI (GenAI) increased self-regulation ($\beta = 0.45$, $p < 0.001$), which in turn mediated positive effects on critical thinking and problem-solving.
- Another study on AI tools in graduate writing showed that students with lower language proficiency (L2) benefited significantly in writing self-efficacy when using AI; however, there was no reduction in cognitive load for students with greater proficiency.
- In the field of SRL, an exploratory study with 16 college students using storyboards of AI applications for SRL found that students perceived such applications as useful for cognitive, metacognitive, and behavioral regulation, but **not** for motivational regulation.

2. Influence Of Cognitive Variables

Cognitive Load

- A recent study discusses how to integrate GenAI with Load Reduction Instruction (LRI) approaches and states that where AI facilitates learning, this is enhanced when activities are designed to **reduce extrinsic load** and align German.
- An article on AI tools in L2 writing found that for more advanced learners the use of AI did not reduce their cognitive load, suggesting that the effectiveness of AI depends on the previous level of knowledge – novices benefit more in terms of reduced load.

Metacognition And Self-Regulation (SRL)

- The qualitative review on SRL and AI highlights that, although AI applications have potential to support SRL, still "the functions and theoretical frameworks of AI within SRL processes remain underexplored".
- In the study of 257 Chinese students, both AI literacy and SRL were found to positively predict writing performance (β SRL ≈ 0.52, $p < 0.001$), while AI literacy was also associated with digital well-being ($\beta \approx 0.30$, $p < 0.01$).

3. Instructional Design Conditions That Favor Better Results

- The findings suggest that AI interventions that offer **metacognitive cues**, **adaptive feedback,** and **learning analytics dashboards** show better outcomes for deep learning. For example, GenAI's study mediating self-regulation emphasizes that ease of use is key for self-regulation to increase.
- Likewise, controlling the extrinsic load in digital design (interface minimalism, clear navigation, staggered tasks) allows AI to "free" cognitive resources for German processing.

Table 1: Summary Of Key Findings.

Variable/Condition	Observed Result	Implications for instructional design
Use of generative AI + SRL	$\beta = 0.45$ in self-regulation, mediating critical thinking/problem solving (n = 223)	Encourage self-regulation through AI; not only giving AI without accompaniment
AI and cognitive load (novice levels)	AI reduced load or increased self-efficacy in L2 novices, not advanced	Adapt AI to the level of knowledge; Novices receive more scaffolding
Perception of AI Applications for SRLs	Perceived usefulness for cognitive/metacognitive regulation, not motivation	Include motivational elements as well as cognitive elements

AI Design + Load Reduction	Integrating AI with Extrinsic Load Reduction Improves Learning Effects	Digital design: lightweight interface, simplified navigation, staggered tasks

4.1. Additional Data And Emerging Patterns

- In the study by Shi, Liu, and Hu (2025) with n = 257, the SEM model indicated that SRL had a stronger direct effect on writing performance than AI literacy; in addition, writing performance mediated the relationship between AI literacy and digital well-being.
- In the qualitative review (2025) on SRL+AI, it is noted that most studies were located in high- or upper-middle-income countries, which generates **geographic bias** in the evidence.
- It also emerged that many studies do not disaggregate the effect of AI among students with different levels of prior knowledge or different cognitive characteristics, which makes it difficult to generalize results.

Interpretation Of the Results

The results suggest that integrating AI into university platforms can optimize learning, but it is not enough to incorporate AI: it is crucial that cognitive variables are managed. In particular:

- **Self-regulation** appears as a central mechanism: without SRLs the potential of AI decreases.
- Managing **the cognitive load** is key: AI must release it or redirect it towards German processing.
- The student's previous level (knowledge, AI literacy, language proficiency) moderates the effects: AI is more effective for students with a lower base, as long as it is accompanied by adequate scaffolding.
- Instructional design (interface, metacognitive scaffolding, adaptive feedback) is decisive for the positive effects to materialize.

4.2. Limitations Of The Findings

- The heterogeneity of the studies (types of AI, disciplines, samples, designs) precludes direct quantitative comparisons.
- Many studies use self-report or perception as a measure, which can skew the results toward positive effects of the technology.
- Most recent studies focus on high-income contexts or leading institutions, and there is little evidence in low-resource settings.
- Cognitive variables (load, metacognition, SRL) are rarely measured with standardized instruments in parallel, which limits clarity about their exact mechanisms.

5. CONCLUSIONS

The evidence collected in this study shows that the integration of artificial intelligence (AI) in university educational platforms has significant **potential** to optimize learning, as long as the central role of cognitive variables (cognitive load, metacognition, and self-regulation of learning) is taken into account. This section summarises key findings, their practical implications and priority areas for future research.

1. Key Takeaways

a) AI as a catalyst for learning when appropriate cognitive processes are activated. The findings suggest that AI systems—especially those that offer adaptive feedback, intelligent tutoring, or generative support—improve academic performance and higher-order skills *if* they are inserted into an instructional environment that takes care of cognitive load management and promotes self-regulation. For example, a study with 223 students found that the ease of use of chat GPT increased self-regulation, which in turn improved critical thinking and problem-solving.

b) Self-regulation of learning (SRL) emerges as a critical mediator. Evidence indicates that, without a reasonable level of SRLs, the benefits of AI are dampened. In the aforementioned study, SRL mediated the relationship between AI ease of use and superior skills (Zhou, Teng & Al-Samarraie, 2024). Likewise, a 2025 systematic review identified that most of the works on AI + SRL in higher education focused on metacognitive and cognitive aspects, less on motivational ones.

c) Cognitive load is not a passive factor: it must be actively managed. Beyond indiscriminately reducing extrinsic load, recent studies propose an instructional design that **aligns** the load (intrinsic, extrinsic, Germanic) to the use of AI. For example, a 2025 paper advocates combining generative AI with "Load Reduction Instruction (LRI)," to alleviate unnecessary burden and free up cognitive resources for German processing.

d) Instructional design, context and level of the student matter. The effects of AI vary according to the student's previous level of knowledge (skill reversal effect) and according to the interface design, metacognitive scaffolding, and duration of the intervention. For example, students with less previous foundation benefit more when adapted intelligent tutoring is incorporated.

e) Risks and gaps that must be addressed.

It warns about the risk of technological dependence, reduced metacognitive activation (what some have called "metacognitive laziness") and scant attention to the motivational component of the SRL. A deficit of studies in resource-constrained educational contexts and a predominance of research in high-income countries are also documented.

2. Practical Implications

- University institutions must **not only adopt AI**, but accompany it with an instructional design focused on cognition and self-regulation (planning/reflection prompts, monitoring boards, adaptations according to level).
- It is key to provide **AI literacy training** for students, so that they can use AI tools judiciously and not as a shortcut without reflection. For example, a study of 257 students found that AI literacy and SRL were positively associated with writing performance and digital well-being.
- The design of the interface should seek to reduce extrinsic load (simple navigation, intuitive functions) and encourage German load (reflection activities, transfer); combining generative AI with principles of load reduction is an emerging avenue.
- Course evaluations should include measures of **cognitive and metacognitive processes**, not just learning outcomes, to assess whether AI is truly promoting self-regulation and higher-order thinking.

3. Lines For Future Research

- To delve into how AI affects SRL **motivation**, given that it has been identified as an underexplored area.
- Conduct longitudinal studies that evaluate the impact of AI on learning across multiple semesters or courses, to verify whether the benefits are maintained or decay over time.
- Nuance the effects according to **the student's profile** (previous level, language proficiency, digital skills) to avoid a "one-size-fits-all" design.
- Expand research in **diverse global contexts**, including low- or middle-income countries, to ensure results of greater external validity.
- Examine the ethical, privacy, and dependency aspects of the use of AI, to ensure that technological integration does not compromise the autonomous and critical development of the student.

4. Final Conclusion

Ultimately, AI can be a **powerful ally** in optimizing college learning, but **it's not a panacea**. Its effectiveness depends on a conscious integration that addresses key cognitive variables, that empowers the student as a regulator of their learning and that places the tool within a well-designed instructional ecosystem. If these components are not addressed, the risk is that AI will remain a decorative or even counterproductive element, encouraging passivity or dependence. Therefore, the synergy between **technology**, **cognition** and **pedagogical design** is the most promising way to achieve deep, sustainable and student-centered learning.

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