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Beyond the algorithm: a bibliometric map of AI in self-regulated learning (2020–2025)

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Abstract

This bibliometric study maps the intellectual structure of artificial intelligence (AI) in self-regulated learning (SRL) from 2020 to 2025. Analyzing 636 Scopus documents through co-occurrence and citation analysis, the research identifies a paradigm shift from adaptive systems toward generative AI and large language models. Results reveal seven thematic clusters, with SRL as the central node, and highlight AI's dual role: it provides automated feedback for SRL phases yet risks inducing "metacognitive laziness" and cognitive offloading. Citation analysis confirms the teacher's critical role as a motivator and mediator in human-AI collaboration. Temporal analysis shows rapid evolution toward generative AI and AI literacy. The study uncovers significant research gaps in explainable AI (XAI), domain-specific implementations, and acceptance factors. We conclude that effective learning requires a balanced triadic partnership among student, AI, and teacher to foster genuine autonomy rather than dependency. This research provides a strategic roadmap for developing ethical pedagogical frameworks in AI-enhanced education.

Keywords

Artificial Intelligence;
Bibliometric Analysis;
Generative AI;
Self-Regulated Learning;
Teacher Support

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Introduction

Over the past decade, digital transformation has fundamentally reshaped the educational landscape, marked by a dramatic shift from static Computer-Assisted Learning (CAL) to dynamic and adaptive Artificial Intelligence (AI) systems (Molenaar, 2022b). This development is accelerated by the capability of Generative AI (GenAI) to not only deliver but also create content and provide intelligent, data-driven action recommendations, thereby unlocking new potential for personalized learning (Afzaal et al., 2021; Xia et al., 2024). In this new era, often referred to as the "Hybrid Human-AI" phase, technology has evolved beyond a mere content distribution tool into a pedagogical agent capable of intelligent interaction with learners (Azevedo et al., 2022; Molenaar, 2022a). This evolution is driven by rapid advancements in data-driven learning models and AI-based language technologies, which enable systems to deliver immediate, personalized feedback (Han et al., 2022). Consequently, the global research focus has shifted to aligning these intelligent systems with human cognition to create collaborative, rather than competitive, learning ecosystems (Molenaar, 2022a; Xinyu Lu & Yanyi Wu, 2024).

Amidst this wave of digitalization, students' ability to self-manage their learning processes, or Self-Regulated Learning (SRL), has emerged as the most crucial competency. Literature emphasizes that successful learners in the digital age are not necessarily the most technically adept, but those who can autonomously set goals, monitor progress, and reflect on their learning outcomes (Azevedo et al., 2022). Therefore, AI-based educational design increasingly incorporates principles such as goal setting, adaptive feedback, and personalization to actively support these SRL phases (Chang et al., 2023; Jin et al., 2023). However, the greatest challenge is that this self-regulation process is often difficult for students to achieve without external scaffolding, especially in minimally supervised online learning environments (Molenaar, 2022a). This is where AI is expected to act as a "cognitive partner," providing personalized and timely scaffolds based on real-time analysis of student learning data to detect difficulties and offer support (Lim et al., 2023; Ng et al., 2024). Therefore, the current urgency in AI development is no longer merely about answer automation, but about the system's ability to detect students' self-regulatory failures and provide timely interventions to foster such autonomy (Azevedo et al., 2022).

Although the potential of AI in supporting SRL is highly promising, the massive integration of Generative AI (GenAI) presents a serious cognitive paradox. On one hand, AI offers efficiency; on the other, there is a tangible risk of diminished critical thinking capacity. This risk includes the potential emergence of "metacognitive laziness," where students become less motivated to engage in deep, independent planning, monitoring, and evaluation of their own learning processes (Fan et al., 2025). León-Domínguez (2024) identifies this phenomenon as "cognitive offloading," a condition where learners tend to delegate information processing burdens to algorithms rather than processing them in their own working memory. Empirical evidence for this theoretical concern is offered by Gerlich (2025), who identified a significant inverse relationship between the frequency of AI tool usage and critical thinking performance among 666 individuals representing various educational stages. This finding reinforces Ivanov's (2023) warning about the "dark side" of technology adoption, which potentially risks creating a generation of passive learners with acute technological dependency.

To address the dilemma between technological efficiency and cognitive autonomy, the role of human support remains irreplaceable. Recent studies highlight a sharp perceptual divide on this issue. Smolansky et al. (2023) found that while educators strive to adapt assessments to foster higher-order thinking with AI assistance, students experience anxiety that using GenAI will stifle their original creativity. This gap underscores the profound transformation GenAI brings to assessment practices, demanding their reconstruction to measure authentic learning outcomes in the era of human-AI

collaboration (Xia et al., 2024). This tension indicates that technology alone is insufficient. Chiu et al. (2023) demonstrated that students' intrinsic motivation to learn with AI heavily depends on teacher support in fulfilling their psychological needs for relatedness and competence. In other words, AI technology will only effectively support autonomy when positioned as a dialogic partner within a pedagogy framework guided by teachers (Afzaal et al., 2021).

Despite numerous partial studies on cognitive impacts and motivational aspects, the current literature remains fragmented. Järvelä et al. (2020) emphasize that collaborative learning regulation processes are often invisible, while technical research tends to focus more on cloud infrastructure efficiency and computational workload prediction (Kumar et al., 2021). Consequently, a fragmented body of research has emerged: one strand delves into algorithms and technical applications, while another explores pedagogical and psychological impacts, lacking a strong integrative framework to unify findings from both domains. A systematic review of the literature confirms that to date, there has been no comprehensive bibliometric mapping that globally visualizes how the interaction between "cognitive risk," "pedagogical support," and "GenAI technology" has evolved post the ChatGPT explosion. The absence of this intellectual roadmap makes it difficult for researchers to identify accurate research trend directions. Furthermore, it remains unclear how major research clusters (such as system design, implementation studies, and cognitive impact analysis) interrelate and evolve.

Accordingly, this study seeks to address this gap by analyzing the intellectual structure of the field through bibliometric methods, thereby offering strategic guidance for future developments in education. More precisely, this study aims to: (1) map the intellectual structure and thematic clusters of research on learning autonomy in the AI era; (2) examine how research trends evolved from 2020 to 2025, with particular attention to the period following the emergence of GenAI; and (3) identify research gaps that warrant further investigation. This bibliometric mapping is intended to serve as a roadmap for designing ethical and effective pedagogical frameworks within an increasingly automated educational landscape.

Methods

This study conducts a bibliometric analysis to explore the intellectual landscape and the development of research trends related to AI-assisted learner autonomy. Bibliometric analysis is recognized as a robust scientific method that enables a quantitative and comprehensive evaluation of a large corpus of scholarly literature, allowing researchers to visualize the development of a field, identify key themes, and uncover patterns of scholarly communication (Donthu et al., 2021). This method enables researchers to construct a high-level overview of the knowledge domain, which in turn provides a strategic basis for defining subsequent research agendas.

Database Selection

For the purposes of this research, Scopus was employed as the main database, given its status as a leading indexing service with rigorous inclusion criteria and wide coverage of peer-reviewed journals in social sciences and educational technology (Mongeon & Paul-Hus, 2016). These characteristics make Scopus particularly suitable for bibliometric investigations and ensure access to the core literature required for a robust and trustworthy analysis of the research field.

Data Collection

To enhance the transparency, systematic nature, and reproducibility of the review process, the data collection phase was structured according to the PRISMA guidelines for systematic reviews and meta-analyses (Moher et al., 2009), which are summarized in Figure 1.

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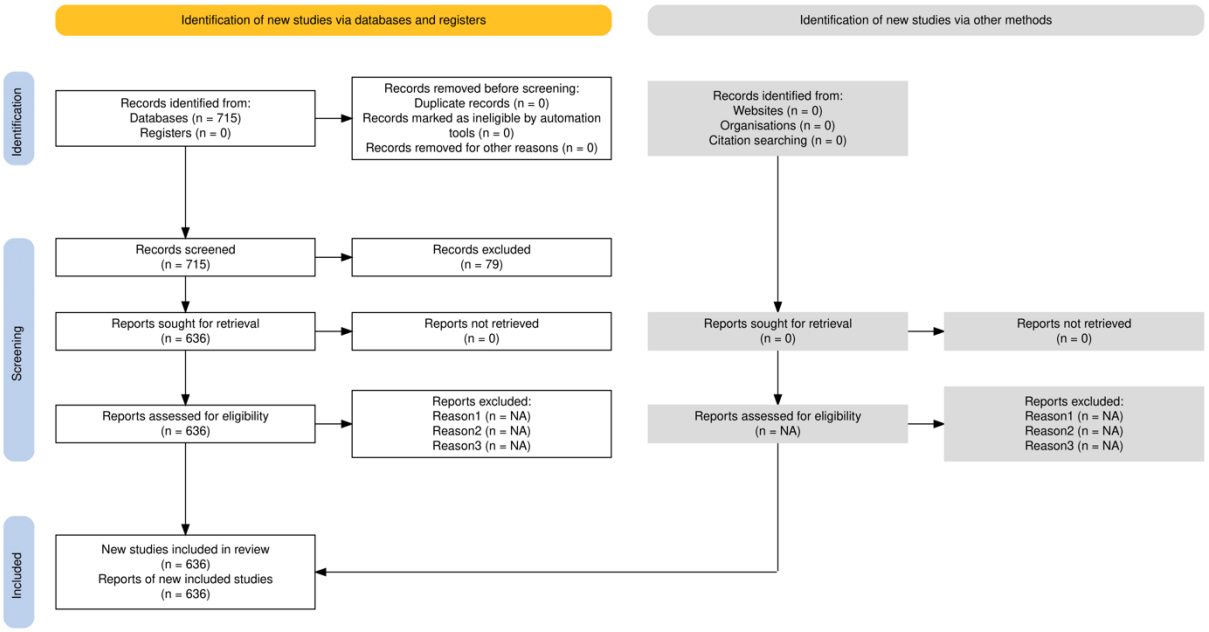


Figure 1. *Overview of the study selection process based on the PRISMA 2020 flow diagram*

Relevant literature was retrieved by formulating and executing a Boolean search query in the Scopus database on December 10, 2025. The applied search string was: ("Artificial Intelligence" OR "AI" OR "Generative AI" OR "ChatGPT") AND ("Self-regulated learning" OR "Learning autonomy" OR "Self-directed learning") AND ("Education" OR "Student"). The search initially identified 715 records, which were then screened and assessed for eligibility using the eligibility criteria summarized in Table 1.

Table 1. Eligibility Criteria for Study Selection

Criterion	Inclusion	Exclusion
Time Range	2020 – 2025	Published before 2020
Document Type	Journal Articles, Conference Proceedings	Editorials, Notes, Errata, Book Chapters, Review Papers
Language	English	Non-English
Thematic Focus	Intersection of AI technology (including GenAI) and learner autonomy	Thematically irrelevant (e.g., AI in healthcare, autonomy in non-educational contexts)

Following this protocol, 79 records were excluded during the screening phase, primarily for being off-topic. The full texts of the remaining 636 records were retrieved, and all met the eligibility criteria. Consequently, these 636 documents constituted the final corpus for bibliometric analysis.

Data Analysis

The bibliometric analysis was performed using VOSviewer (version 1.6.20), a dedicated application for building and visualizing bibliometric networks derived from scientific literature (van Eck & Waltman, 2010). A dataset of 636 documents was downloaded from Scopus in plain-text format and subsequently imported into VOSviewer for processing. The analysis focused on keyword co-

occurrence to reveal the conceptual structure of the research area. Keywords were taken from the Title field and analyzed using the binary counting method to maintain analytical accuracy. Setting a minimum occurrence of 5 resulted in 47 keywords, which constituted the nodes of the network.

To interrogate the data comprehensively, multiple visualization techniques were employed. First, a Network Visualization map was generated to identify the main research clusters and analyze the strength of links between key terms, revealing the core thematic structure. Second, an Overlay Visualization map was created by coloring keywords based on their average publication year. This technique was crucial for tracing the temporal evolution of research focus, particularly highlighting trends and emerging topics in the period of 2024–2025 following the proliferation of Generative AI tools. Finally, a Density Visualization map was utilized to assess the conceptual maturity and saturation of research areas, where regions of high density indicate well-explored topics and areas of low density highlight potential, underexplored research gaps. Collectively, these visualizations provide a solid, multidimensional view of the research landscape where artificial intelligence and learner autonomy intersect.

Results and Discussions

Bibliometric Profile and Key Terminology Landscape

This study consolidates a final dataset of 636 documents indexed in Scopus (2020–2025) through a systematic PRISMA protocol. Co-occurrence analysis (keyword co-occurrence) of document titles extracted 47 main key terms. The term Self-Regulated Learning (SRL) emerged as the most dominant node with 33 occurrences and the highest relevance score. This dominance confirms that learner autonomy is the most crucial dependent variable in the current AI literature, where technology is positioned to strengthen the learner's internal regulatory capacity.

The data in Table 2 show that the terms Feedback (21) and Assessment (17) have very high relevance scores. This suggests that, in the existing literature, the most widely acknowledged technical role of artificial intelligence is its capacity to automate formative feedback cycles, which are a crucial element of the self-monitoring phase in the self-regulated learning process.

Table 2. Analysis of Keyword Frequency and Strategic Relevance Scores

No	Term	Occurrences	Relevance Score	Strategic Insight
1	Self Regulated Learning	33	7,125	The core focus of student autonomy.
2	Technology	25	3,206	The primary infrastructure supporting AI.
3	Feedback	21	9,616	The main mechanism of AI in SRL support.
4	Systematic Review	21	5,887	Dominant methodology in this domain.
5	Teaching	21	4,879	Focus on the instructional environment.
6	Design	19	6,800	Development of intelligent systems.
7	Assessment	17	9,753	Automated evaluation of learning processes.
8	Self Regulation	14	6,153	Supporting psychological variables.

No	Term	Occurrences	Relevance Score	Strategic Insight
9	Case Study	14	3,847	Predominant field research approach.
10	Generative AI	13	6,846	Emerging technology trend (2024-2025).

Intellectual Foundation: Citation Analysis and Scholarly Conversation

The appeal and influence of a research topic can be seen in how often its key articles are cited. Citation counts reported in this section are based on Google Scholar data accessed on 10 December 2025. Table 3 shows that the literature on AI and SRL is highly dynamic, with articles published in 2023 and 2024 having garnered hundreds of citations in a short time.

Among the examined publications, Chiu et al. (2023) is the most influential study, with 759 citations, demonstrating that teacher support is a crucial predictor of students' motivation in AI-based learning environments. This result underlines that technology cannot replace the educator's role; instead, it necessitates a deliberately structured partnership between humans and AI.

In parallel, a critical line of discussion has emerged around the cognitive risks associated with AI. The study by Fan et al. (2025), which coined the term 'metacognitive laziness' (330 citations), cautions that effortless access to information through AI can diminish the level of cognitive effort needed for deep learning. This concern aligns with the findings of León-Domínguez (2024) regarding the potential weakening of executive functions due to excessive dependence on virtual assistants.

Table 3. Top 10 Most Influential Articles by Citation Count (2020-2025)

No	Author (Year)	Shortened Title	Key Findings	Citations
1	Chiu et al. (2023)	Teacher support & AI-chatbot motivation...	Student drive and engagement while utilizing AI chatbots are heavily influenced by the guidance provided by educators.	759
2	Wei (2023)	Impact of AI on English instruction...	Incorporating intelligent tools in linguistic education significantly boosts academic success, internal drive, and autonomous study habits.	598
3	Chang et al. (2023)	AI chatbot design for supporting SRL...	To facilitate self-regulation, the development of AI chatbots should prioritize tailored feedback and objective-setting features.	417
4	Fan et al. (2025)	Cognitive risks of generative AI...	The deployment of generative AI risks fostering a decline in critical thinking depth, which can hinder the overall instructional flow.	330
5	Nguyen et al. (2024)	Human–AI collaboration in writing...	This research highlights optimized interaction frameworks between individuals and AI to improve scholarly writing performance.	324

No	Author (Year)	Shortened Title	Key Findings	Citations
6	Jin et al. (2023)	AI tools for supporting online SRL...	Various smart applications have proven beneficial in assisting learners with managing their independent progress within virtual classrooms.	317
7	Xia et al. (2024)	Review of generative AI in assessment...	Scholarly evaluation models are undergoing substantial shifts due to the automated and highly customized systems enabled by GenAI.	270
8	Ng et al. (2024)	Empowering SRL using ChatGPT...	When integrated with sound pedagogical strategies, ChatGPT serves as a powerful tool for bolstering student self-governance.	247
9	Lee et al. (2024)	Guidance systems for ChatGPT...	Structured support systems are essential for maximizing AI effectiveness in fostering complex reasoning and information synthesis.	206
10	Dahri et al. (2024)	Acceptance of AI-powered ChatGPT...	Learners' adoption of ChatGPT for self-regulatory purposes depends on how it is integrated into pedagogy.	176

Network Mapping: Cluster Structure and Topic Interaction

Figure 2 visualizes the co-occurrence network map of the 47 key terms, revealing the intellectual structure of this domain divided into five interrelated thematic clusters.

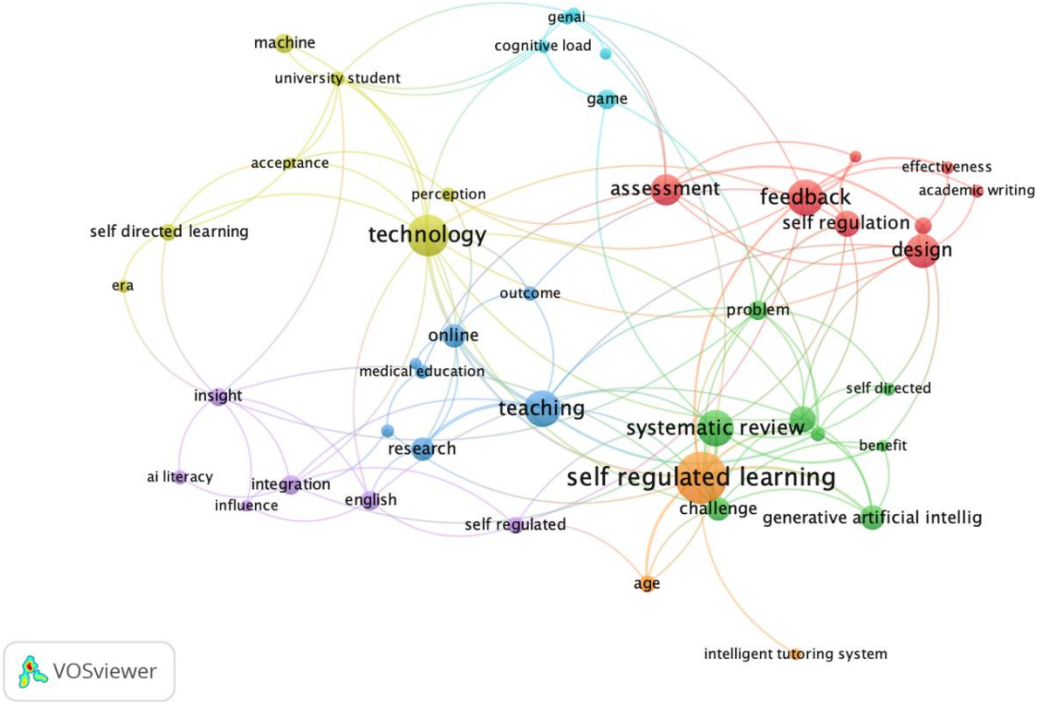


Figure 2. *Keyword Co-occurrence Network in AI-Supported Self-Regulated Learning (2020–2025)*

The network map presented in Figure 2 shows that the 47 primary terms are grouped into seven distinct thematic clusters, illustrating the multidimensional complexity of AI integration in autonomous learning.

Cluster 1 (Orange): The Core of Learning Autonomy. With Self-Regulated Learning serving as the central node, this cluster acts as the primary hub connecting the entire research network. It encompasses related concepts such as *challenge*, *age*, and *intelligent tutoring systems*, establishing a foundational focus on the learner's internal regulatory processes within AI-supported environments (Azevedo et al., 2022; Molenaar, 2022b).

Cluster 2 (Red): Support Mechanisms and Automated Evaluation. This cluster highlights the crucial, strong link between Feedback and Assessment, connected to terms like *design*, *self-regulation*, *effectiveness*, and *academic writing*. This pattern provides visual proof of the scholarly consensus that AI's primary role is to act as scaffolding, offering automated, formative feedback to enhance learning (Chang et al., 2023; Xia et al., 2024).

Cluster 3 (Yellow): Technological Infrastructure and User Perception. Centered on Technology, this cluster includes terms like *acceptance*, *perception*, *machine*, *university student*, and *self-directed learning*. It represents a significant research stream focused on adoption prerequisites, emphasizing technological infrastructure and the psychological factors influencing how users accept AI tools (Chiu et al., 2023; Dahri et al., 2024).

Cluster 4 (Green): Methodological Synthesis and Impact. This cluster connects Systematic Review with *generative artificial intelligence*, *benefit*, *self-directed*, and *problem*. Its structure indicates that a substantial portion of the current literature involves synthesizing evidence to weigh the reported benefits against identified challenges in AI integration (Wei, 2023; Xia et al., 2024).

Cluster 5 (Light Blue/Cyan): The Emergent Generative AI Paradigm. Positioned distinctly in the upper part of the map, this cluster contains cutting-edge terms like GenAI, Cognitive Load, and Game. It represents the new, post-ChatGPT research frontier that critically examines the cognitive demands and potential risks, such as "metacognitive laziness," associated with generative AI applications (Fan et al., 2025; León-Domínguez, 2024).

Cluster 6 (Dark Blue): Specialized Instructional Environments. This cluster groups Teaching, Online, Research, and Medical Education. It underscores the application of AI within specific instructional contexts, particularly highlighting the exploration of online settings and high-stakes professional fields (Han et al., 2022; Kumar et al., 2021).

Cluster 7 (Purple): Future Insights and Ethical Integration. Located on the lower left, this forward-looking cluster links Insight, AI Literacy, Integration, and English. It captures the emerging emphasis on ethical awareness and system transparency as prerequisites for responsibly integrating AI (Afzaal et al., 2021; Ng et al., 2024).

The visualization confirms Self-Regulated Learning (Cluster 1) as the gravitational center of the field (Azevedo et al., 2022). The strong linkage between Feedback (Cluster 2) and SRL validates the dominant narrative of AI as a feedback provider (Molenaar, 2022a). Simultaneously, the presence of distinct clusters for User Perception (3), Generative AI (5), and AI Literacy (7) maps the field's expansion into critical dimensions of adoption psychology, emerging technology, and ethical competency (Dahri et al., 2024; Ng et al., 2024). The separate methodological and contextual clusters further illustrate the maturation of the domain through evidence synthesis and specialized application

Temporal Evolution and Paradigm Shift

Figure 3 employs an overlay view that colours each keyword node according to its average year of appearance in the literature, which helps to reveal shifts in the dominant themes across the period studied.

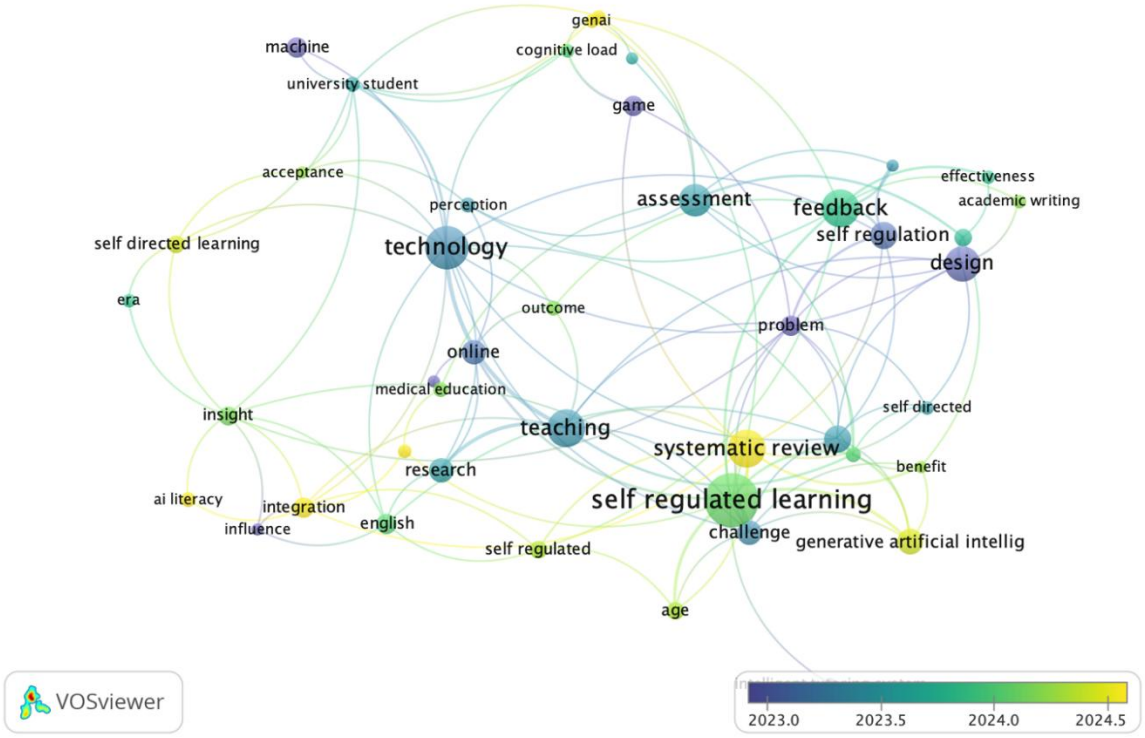


Figure 3. *Time-Based Overlay Visualization of Keyword Co-occurrence*

Initial Focus (2023.0): Early research in this timeframe was dominated by foundational concepts such as online learning, design, and perception, represented by dark blue nodes. These studies primarily explored the basic instrumental effectiveness and structural design of technology-enhanced learning environments.

Paradigm Shift (2024.5): A sharp paradigm shift is evident toward the end of the period, with bright yellow nodes such as "GenAI" and "AI Literacy" becoming prominent. This color transition highlights a critical shift from asking whether AI helps toward investigating the ethical competencies and cognitive engagement required for effective human-AI interaction (Fan et al., 2025; Ng et al., 2024).

Emergent Themes: The recent emergence of terms like "Insight" and "Integration" (in yellow) suggests that the current scholarly discourse has moved into a more nuanced phase, focusing on how Large Language Models (LLMs) can be responsibly woven into the fabric of higher education to support genuine student autonomy rather than fostering dependency (Dahri et al., 2024; Xia et al., 2024).

Identification of Research Gaps through Density Analysis

Figure 4 serves as a strategic map to identify saturated research areas and existing gaps through density analysis.

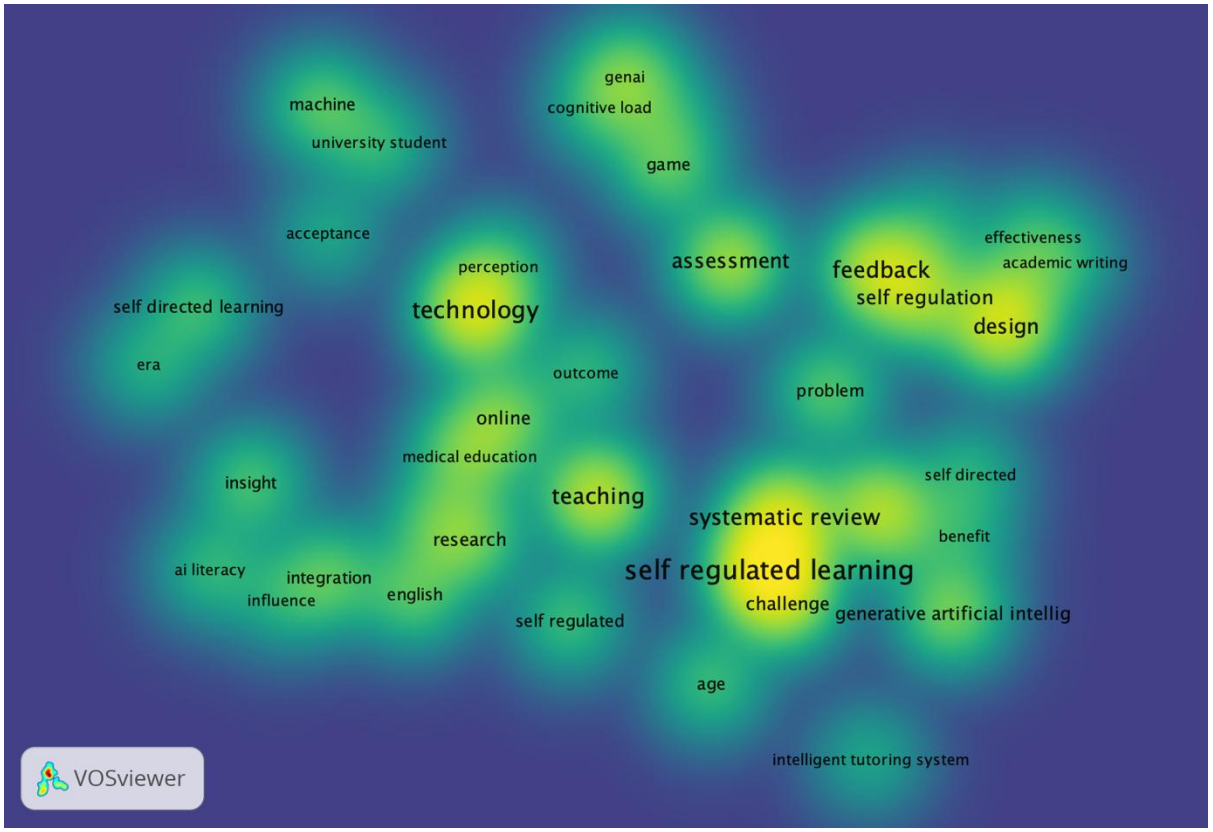


Figure 4. *Topic density landscape in AI-supported self-regulated learning*

The density visualization in Figure 4 provides a clear topography of the research landscape. The brightest, most saturated areas are predictably centered on the field's foundational pillars: Self-Regulated Learning (SRL), Technology, and Teaching. This intense luminosity confirms that the initial core topics have been extensively explored and form the well-established terrain of the current academic discourse.

Conversely, the map's strategic value lies in its illumination of the "cold spots"—areas of low density that reveal critical research gaps. Most notably, the conceptual spaces surrounding user Acceptance and behavioral factors remain underexplored. This gap underscores a pressing need to move beyond studies of efficacy and delve deeper into the psychological variables influencing tool adoption, a direction explored by recent work such as that of Dahri et al. (2024). Adjacent to this is the faint presence of AI Literacy. The low density of this node indicates that the scholarly conversation regarding the ethical understanding and critical competencies needed to navigate AI systems is still in its infancy (Ng et al., 2024). Finally, the sparse coverage of specialist educational contexts, such as Medical Education, exposes a significant "generalization bias". This gap suggests that findings from generalized learning environments are often presumed to apply directly to high-stakes professional domains, potentially overlooking unique scaffolding and competency requirements (Xia et al., 2024).

Through this multidimensional analysis, the field appears highly dynamic: scholars largely agree that AI's central contribution lies in providing feedback to support SRL (Chang et al., 2023; Jin et al., 2023), yet this consensus is accompanied by increasing concern over cognitive risks (Fan et al., 2025; León-Domínguez, 2024) and a pronounced turn toward Generative AI (Ng et al., 2024). At the same time, the detected gaps in studies of acceptance, AI literacy, and context-specific implementations delineate a clear research trajectory for subsequent work (Dahri et al., 2024; Ng et al., 2024).

The Dual Nature of AI in SRL: Between Scaffolding and Cognitive Offloading

The bibliometric mapping reveals a fundamental tension that has come to define the field of AI-supported self-regulated learning. On one hand, there is a strong consensus that AI functions as a feedback automation system, as discussed by Chang et al. (2023), which supports the monitoring and control phases of SRL, a view that is further reinforced by Jin et al. (2023). The prominence of *Feedback* and *Assessment* as central nodes confirms this technological framing, which aligns with established theories of formative assessment as crucial for self-regulation (Panadero, 2017; Zimmerman, 2000). This perspective positions AI as what Azevedo et al. (2022) term a "metacognitive tool" – an external scaffold that can model and support regulatory processes that learners have not yet internalized.

However, the emergence of the distinct Generative AI cluster and the influential work on "metacognitive laziness" (Fan et al., 2025; León-Domínguez, 2024) challenges this optimistic narrative. The risk identified here is not merely technical but epistemological: when AI systems become capable of generating not just feedback but entire cognitive products (plans, analyses, syntheses), they risk creating what Roll & Wylie (2016) warned about in intelligent tutoring systems – procedural competence without conceptual understanding. This concern echoes earlier critiques of technology in education that warned of "cognitive offloading" without corresponding cognitive development (Sweller, 2020). The empirical findings by Gerlich (2025), indicating an inverse relationship between AI usage and critical thinking performance, provide troubling evidence that this theoretical risk has begun to materialize.

The Teacher as Essential Mediator: Orchestrating the Human-AI Partnership

The most frequently cited study in this corpus, Chiu et al. (2023), challenges technologically deterministic views by showing that the level of guidance provided by teachers is the key factor shaping students' motivation in AI-supported learning settings. This finding is consistent with a large body of educational research showing that the quality of teacher–student relationships has a significant impact on students' engagement and academic performance (Hattie, 2008; Roorda et al., 2011). It also converges with technology-integration studies that frame teachers as instructional architects who design and orchestrate learning with digital tools (Mishra & Koehler, 2006; Tondeur et al., 2017).

This evidence supports what Molenaar (2022a) conceptualizes as "hybrid human-AI regulation," where technological and human supports are not merely additive but synergistic. In this model, teachers fulfill roles that AI cannot: providing emotional scaffolding (Pekrun, 2019), fostering the conditions for epistemic agency (Damşa et al., 2021), and creating dialogic spaces where students can articulate and refine their thinking (Mercer, 2019). As Luckin & Cukurova (2019) argue, the most effective educational AI systems are those designed to "amplify rather than replace" the teacher's expertise. This is consistent with recent implementation research indicating that AI tools are most effective when they are integrated into instructional designs led and orchestrated by teachers (Holstein et al., 2019; Ouyang & Jiao, 2021).

The Transparency Deficit: Explainable AI as a Prerequisite for Trust

The bibliometric analysis reveals a concerning gap in research on Explainable AI (XAI) in educational contexts. This absence is particularly significant given growing calls for "algorithmic transparency" in educational technology (Baker & Hawn, 2022; Williamson, 2017). Research in human-computer interaction consistently shows that system transparency is crucial for user trust and appropriate reliance (Leichtmann et al., 2023; Shin, 2021), yet our bibliometric analysis suggests this consideration has been largely absent from discussions of AI in SRL.

This gap is problematic because, as research in educational data mining has shown, black-box algorithms can perpetuate biases and make errors that are invisible to users (Holmes et al., 2022). Within self-regulated learning (SRL) settings, where the goal is to develop students' metacognitive awareness, opacity in AI systems creates Knight & Buckingham Shum (2017) term a "pedagogical black box" – students receive feedback or recommendations without understanding the reasoning behind them, limiting their ability to develop independent judgment. Emerging work in XAI for education suggests potential solutions, such as providing confidence indicators (Kaser et al., 2017) or counterfactual explanations (Leichtmann et al., 2023), but our analysis indicates this remains a nascent area requiring substantial development.

The Contextualization Gap: Moving Beyond Disciplinary Generalization

The sparse representation of specialized educational contexts (such as medical education) in the bibliometric map reveals what we term disciplinary generalization bias – the assumption that findings from general educational contexts apply equally across domains. This bias is particularly problematic given evidence that epistemic practices (Kelly, 2008) and regulatory strategies (Greene et al., 2018) vary significantly across disciplines.

Research on professional education emphasizes that situated cognition (Lave & Wenger, 1991) and adaptive expertise (Hatano & Inagaki, 1984) require domain-specific approaches to regulation. In medical education, for instance, SRL must account for the high-stakes decision-making and ethical dimensions (Lingard, 2007) that differ from general academic contexts. Similarly, in STEM fields, where problem-solving often involves iterative experimentation, AI support for SRL might need to focus more on hypothesis generation and experimental design (Worsley & Blikstein, 2018). These discipline-specific issues receive minimal attention in the current body of work, leaving a notable gap in our knowledge of how AI-based SRL support should be adapted for different educational contexts.

Synthesizing the Challenges: A Roadmap for Future Research

Building on the findings, several directions warrant further investigation to advance research on AI-supported self-regulated learning (SRL). Future studies should examine the long-term cognitive impact of AI-supported SRL through longitudinal designs involving multiple measurement points to determine whether AI-based scaffolding facilitates the internalization of self-regulatory skills, as anticipated by Vygotskian theory, or instead increases learners' dependence on AI support, as suggested by research on metacognitive laziness. Such investigations should incorporate multimodal data to capture changes in both cognitive processes and affective states (Järvelä et al., 2020).

Further research should also focus on developing and evaluating explainable artificial intelligence (XAI) interfaces specifically designed for educational contexts. Rather than emphasizing technical explanations alone, these interfaces should provide pedagogically meaningful information that enhances teachers' understanding of AI-driven processes while supporting students' metacognitive development. This direction requires integrating insights from the learning sciences (Sawyer, 2014) and educational psychology (Mayer, 2019) to ensure that AI explanations contribute meaningfully to teaching and learning.

Another important direction concerns the development of domain-specific implementations of AI-supported SRL. Since learning processes and self-regulatory demands vary across academic disciplines, professional fields, and cultural contexts, future research should investigate how AI-supported SRL systems can be adapted to these different settings. Iterative, design-oriented research approaches are particularly relevant for developing, testing, and refining contextually appropriate implementations (Anderson & Shattuck, 2012).

Finally, future research must address the equity and ethical implications of AI-supported SRL. Particular attention should be given to how algorithmic bias may reproduce or intensify existing educational inequalities (Baker & Hawn, 2022; Noble, 2020). Accordingly, researchers should investigate strategies for designing inclusive and equitable AI-supported systems that provide accessible, fair, and context-sensitive support for learners with diverse needs and backgrounds (Kizilcec et al., 2020).

Conclusion

To conclude, this paper draws on a bibliometric analysis to reveal both the intellectual structure and the time-based progression of scholarship on Artificial Intelligence (AI) in Self-Regulated Learning (SRL) across the 2020–2025 period. Through the examination of 636 Scopus-indexed publications, the study portrays a field undergoing dynamic and accelerated change, characterized by a clear paradigm shift towards Generative AI (GenAI). This transformation underscores how crucial it is to understand the intricate ways in which advanced technologies interact with, and potentially shape, the development of learner autonomy.

The network and temporal analyses pinpoint a central, defining tension: a strong, established consensus on AI as an automated feedback provider for SRL coexists with an emergent and critical discourse on cognitive risks, most notably "metacognitive laziness." The intellectual structure confirms that while technology is a dominant force, the most influential scholarship robustly establishes the teacher's indispensable role as a motivator and mediator, forming the cornerstone of a hybrid human-AI regulation model. A significant and concerning finding is the marked scarcity of research on Explainable AI (XAI) for education and the underrepresentation of specialized contexts, revealing a disciplinary generalization bias that risks inappropriate application of findings.

Collectively, these insights motivate the following integrated conclusions and strategic directions for academic investigation and professional practice:

1. Theoretical and Empirical Implications. The field must advance beyond viewing AI as a simple tool. Future theoretical frameworks should formalize the triadic partnership model (student-teacher-AI) and deepen the concept of hybrid regulation. Empirical research must prioritize longitudinal and multi-modal studies to decisively investigate whether AI scaffolding fosters long-term skill internalization or creates dependency, thereby resolving the core tension between support and offloading.

2. Practical Implications for Pedagogy and Design. For educators and instructional designers, successful integration requires pedagogical designs that position AI as a catalyst for critical thinking and metacognitive engagement. This necessitates a foundational investment in developing AI literacy for both teachers (as expert mediators) and students (as empowered, critical users). Furthermore, a major design frontier is pedagogically-grounded Explainable AI (XAI). Research must employ design-based methodologies to create interfaces that make AI reasoning transparent, meaningful, and trust-building for educational stakeholders.

3. Strategic Recommendations for Policy and Research Development. To systematically address the identified gaps, a coordinated effort is required. Funding bodies and institutions should foster interdisciplinary collaborations that bridge learning sciences, computer science, and domain expertise (e.g., medicine, engineering). Policy should incentivize research on ethical design and support professional development in AI literacy. The research agenda itself must actively pursue domain-specific investigations to adapt SRL principles for high-stakes fields and mandate equity-focused audits to detect and mitigate algorithmic bias, ensuring AI promotes inclusive and equitable support.

In summary, this bibliometric analysis provides a strategic roadmap, underscoring that the trajectory of AI in SRL must be steered not by technological capability alone, but by a principled

commitment to pedagogical wisdom and human-centered design. The ultimate goal is to ensure these powerful technologies act as genuine levers for deeper cognitive and metacognitive development, empowering autonomous and resilient learners.

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