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REVIEW ARTICLE

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A systematic mapping review at the intersection of artificial intelligence and self-regulated learning

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Abstract

Recently, artificial intelligence (AI) has increasingly been integrated into self-regulated learning (SRL), presenting novel pathways to support SRL. While AI-SRL research has experienced rapid growth, there remains a significant gap in understanding the intersection between AI and SRL, resulting in oversight when identifying critical areas necessitating additional research or practical attention. Building upon a well-established framework, from Chatti and colleagues, this systematic mapping review identified 84 studies through the Web of Science, Scopus, IEEE Xplore, ACM Digital, EBSCOHost, Google Scholar, and Open Alex, to explore the intersection of AI and SRL within the four key aspects—Who (stakeholders), What (theory), How (methods), and Why (objectives). The main results revealed that AI-SRL research predominantly focuses on higher education students, with minimal attention to primary education and educators. AI is primarily implemented as an intervention—through adaptive systems and personalization, prediction and profiling, intelligent tutoring systems, and assessment and evaluation—to support students' SRL and learning processes. The direct impact of AI on SRL was primarily focused on the metacognitive and cognitive aspects of SRL, while the motivational aspect of SRL remains underexplored. While over one-third of the AI-SRL **s**tudies did not specify an SRL theory, Zimmerman's model of SRL was the most frequently applied among those that did. The use of AI in supporting SRL has extended beyond just focusing on and supporting SRL itself; it has also aimed to enhance various educational and learning activities as end outcomes such as improving academic performance, motivation and emotions, engagement, and collaborative learning. The results of this study extend our understanding of the effective application of AI in supporting SRL and optimizing educational outcomes. Suggestions for further research and practice are provided.

Keywords: Artificial intelligence, AI, Learning analytics, Self-regulation, Self-regulated learning, SRL, Systematic review, Theory

Introduction

There is widespread recognition that self-regulated learning (SRL) stands as a crucial key to becoming a successful lifelong learner (e.g., Järvelä et al., 2016; Schunk & Zimmerman, 2013; Winne, 1995; Zimmerman, 2002). SRL studies strive to explore the nature, origins, and development of how students regulate processes related to learning (Zimmerman & Schunk, 2011) and how such regulation impacts learning processes and outcomes. These efforts over the decades have led to the development of different SRL models to advance our understanding of SRL (see Panadero, 2017) and showcase the impact of SRL on different aspects of learning processes and outcomes including but not limited to satisfaction of learning (Kara et al., 2021), engagement (Doo & Bonk, 2020), academic performance (Ning & Downing, 2012), motivation and self-efficacy (Baars & Wijnia, 2018; Baars et al., 2017).

As technology has increasingly become an integral part of the education system, the intersection of SRL and technology has been an important avenue of research to explore how students' SRL can be supported by technology (Daumiller & Dresel, 2019; Heikkinen et al., 2023) or how students' SRL can be facilitated within technology-enhanced learning environments (e.g., Berglas-Shapiro et al., 2017; Lenne et al., 2008). A recent game-change progress in technology is the evolution of Artificial Intelligence (AI). AI is a broad concept and there are different definitions of AI. For example, AI as intelligent behaviour is described as the study of how to make computers do things at which, at the moment, people are better (Rich & Knight, 1991). This emphasizes AI's goal of enabling machines to replicate tasks that require human intelligence. AI as human-like intelligence is outlined by Russell and Norvig (2010), who define AI as the development of systems that perceive their environment and take actions that maximize their chance of success. This focuses on creating agents that can autonomously interact with their surroundings to achieve specific goals. In this paper, however, we approach AI as a field of study and adhere to the definition put forward by John McCarthy, a pioneering figure in AI, who described it as "the science and engineering of creating intelligent machines, particularly intelligent computer programs" (McCarthy, 2007, p. 2). In this context, "intelligence" implies a machine's capacity to replicate cognitive processes like learning, reasoning, and problem-solving, which are typically associated with human intelligence.

Siemens et al. (2022) argue that the AI advancements have led to the unprecedented ability to even contemplate the existence of a non-human cognition system so-called "artificial cognition" representing a paradigm shift in the intersection of education and technology in general but also SRL and technology in particular. In recent years, AI has been widely integrated into different educational contexts including online education, higher education, and K-12 education (e.g., Doğan et al., 2023; Hartley et al., 2024; Kong & Yang, 2024) which has brought to the forefront the necessity of a critical understanding of its implications for SRL. As a result of this wide integration, research on AI-SRL has grown swiftly, presenting emerging pathways to support SRL.

Currently, research on AI and SRL in educational settings has been directed toward expanding our scientific methods, developing educational technologies and contributing to theory development. For instance, Fan et al. (2022) explored the use of multimodal data to enhance SRL measurements, whilst Wang and Lin (2023) demonstrated the potential of Long Short-Term Memory networks to analyse self-reported protocols and identify cognitive and metacognitive strategies within SRL. With regard to educational technology, Azevedo et al. (2022) developed MetaTutor, an intelligent tutoring system, which uses AI to provide adaptive support for SRL in science learning. With regard to theoretical contribution, we note that there is emerging interest in hybrid intelligence and co-regulation, where researchers start to explore human-AI collaboration as a manifestation of shared regulation (Järvelä et al. 2023a). Conceiving human-AI regulation as an interactive symbiosis, with AI customizing support to suit human needs, enhances the learner's regulatory capabilities. These strands collectively highlight AI's multifaceted role in advancing SRL, suggesting that AI-SRL research commonly takes on multiple forms. These include using AI to measure and analyze SRL (Fan et al., 2022; Molenaar et al., 2023; Noroozi et al., 2019; Wang & Lin, 2023) and to support SRL activities (e.g., personalized feedback and scaffolding strategies) in the form of human-AI collaboration (Chiu, 2024; Järvelä et al. 2023b, 2023c; Molenaar, 2022).

Despite these advancements, scholars emphasize that further research is needed to explore alternative aspects of the AI-SRL intersection and its impact on the performance of both educators and learners. For instance, Siemens et al. (2022) point to the need to advance our understanding of human-AI cognition in learning contexts. Molenaar et al. (2023) emphasize the necessity for robust interdisciplinary collaborations to accelerate advancements in AI-supported SRL. Akinwalere and Ivanov (2022) highlight the necessity for comprehensive insights into AI's impact on learning. This includes examining the methodologies and approaches for effective AI deployment and identifying stakeholders to understand who benefits and who might be disadvantaged by AI advancements. In addition, there are concerns about the alignment between theory and practice in AI-supported SRL. This misalignment may create obstacles in translating research outcomes into practical classroom applications. Kitto et al. (2022) note that this disconnect can lead to skepticism among educators and learners about the reliability and applicability of AI-SRL research findings. A deeper understanding of the AI-SRL intersection could lead to more tailored interventions that effectively embed AI into SRL practices. Moreover, it could help refine existing SRL models and develop new approaches that consider the paradigm shift brought about by AI, empowering learners, promoting metacognitive skills, and fostering autonomous learning behaviors. Therefore, this paper aims to fill these gaps by conducting a systematic literature review that explores the different aspects of the intersection of AI and SRL, utilizing a well-established framework to structure the review.

We found only one review on AI-SRL (Molenaar et al., 2023). This study introduced the SMA Grid, which visualizes data modalities (cognitive, metacognitive, affective) collected from various sources to assess SRL, and describes different analytical approaches (unimodal, horizontal, vertical, integrated) to explain AI's role in measuring SRL. While we acknowledge the significant contributions of this review to the learning sciences, we believe it does not fully capture the AI-SRL intersection for several reasons. First, the framework mainly relies on the authors' own research, which may overlook much of the rapidly growing literature. Second, the SMA Grid emphasizes AI's role in SRL measurement, leaving out other important aspects such as AI's purposes and methodologies in SRL. Third, it provides limited information on the theoretical concepts that underpin AI-SRL studies, which are essential for building trust in AI results among educators and students. Therefore, although the SMA Grid is a valuable starting point, we suggest that a more comprehensive understanding of the AI-SRL intersection is needed. Drawing from the well-established framework by Chatti et al. (2012), we map four key aspects: Who (AI-SRL stakeholders), What (AI-SRL theoretical frameworks), How (AI-SRL implementation), and Why (AI-SRL objectives), to provide a thorough overview of this research intersection. This framework is further elaborated in the following section.

Conceptualizing the review and research questions

To structure our research on the intersection of AI and SRL, we adopted Chatti et al.'s (2012) framework, originally designed for learning analytics (LA). This framework covers four main aspects: Who, What, How, and Why. *Who* refers to the stakeholders targeted by LA, such as students, educators, administrators, and researchers, each with unique perspectives and objectives. *What* focuses on the data used, including learning behavior and emotional data from various environments and technologies. *How* describes the methods and algorithms used in LA, like data mining and visualization. *Why* addresses the objectives of LA, such as providing feedback, assessing engagement, and predicting at-risk students (Banihashem et al., 2022).

Although Chatti et al.'s framework (2012) was originally developed to explain LA systems' aspects, this framework can also be applied to delineate the key aspects of AI systems when considering their application within education. For example, in the context of AI in education, stakeholders encompass various actors such as educators, students, administrators, policymakers, and developers of educational technologies (Bogina et al., 2022; Khosravi et al., 2022). Each stakeholder group may have distinct roles, responsibilities, and expectations concerning the integration of AI systems in educational settings (Khosravi et al., 2022). Concerning the aspect of "*What*", AI systems in education rely on diverse sources of data which can be captured and measured from learning environments (Cope et al., 2021; Fan et al., 2022), ranging from structured student records and assessments to unstructured text, audio, and video content. In terms of "*How*", similar to LA systems, AI systems also rely on certain techniques and methods including machine learning or natural language processing to translate data into knowledge. Considering the "Why" aspect, any AI systems are used in education for a reason. For example, for educators, AI reduces workload (Hashem et al., 2024) by enabling timely, scalable feedback for large classes (Banihashem et al., 2022; Pardo et al., 2019) and enhancing assessment practices (Swiecki et al., 2022). For learners, AI assists in improving writing tasks (Su et al., 2023), developing metacognitive reasoning through AI-driven interactions (Ortega-Ochoa et al., 2024), supporting self-regulation (Afzaal et al., 2024), and promoting engagement, motivation, collaboration, and improved learning outcomes (Huang et al., 2023b).

In this review, we distinguish AI from LA by emphasizing their roles, interaction levels, and functions within educational contexts. AI encompasses intelligent systems designed to replicate human cognitive processes by providing adaptive feedback and direct interventions that actively support and respond to the user need (Dignum, 2019; McCarthy, 2007; Russell & Norvig, 2010) that in this context it is learners' SRL needs. This includes capabilities such as adaptive learning paths, and predictive support, which enable AI to act autonomously on insights and directly enhance SRL. By contrast, LA primarily applies statistical methods and data mining techniques to analyze educational and learning data, revealing insights into learning behaviors without necessarily providing adaptive interventions (Dignum, 2019). Therefore, as noted by Dignum (2019), the critical difference lies in AI's ability to autonomously interact with and adjust to the learner based on insights, while LA supports human decision-makers by interpreting data patterns to understand behaviors and trends. For instance, studies by Cogliano et al. and Tu et al. employed predictive models commonly associated with both AI and LA. However, within our review, they are classified under AI due to their active support for SRL through adaptive, responsive measures, rather than merely interpreting learning data, which is characteristic of LA (Chatti et al., 2012).

Our directed interest concerns SRL. While cognition and metacognition are typically identified as core regulated elements within SRL, there is theoretical variation concerning the regulation of motivation. Specifically, Winne and Hadwin (1998) do not explicitly treat motivation itself as directly regulated; rather, motivation is considered an influential condition that drives or constrains learners' engagement within SRL phases, especially at the onset of tasks. In contrast, Zimmerman (2002) positions motivation as a component regulated by learners alongside cognition and metacognition throughout the entire cyclical SRL process. Zimmerman highlights learners' deliberate use of motivational strategies—such as setting personally meaningful goals, rewarding themselves, and proactively seeking feedback—as integral regulatory actions aimed at maintaining or enhancing motivation to achieve learning goals.

Recognizing the need for a comprehensive overview of AI-SRL, we leverage Chatti et al.'s (2012) to systematically explore the intersection of AI and SRL within the four key aspects—Who (stakeholders), What (theory), How (methods), and Why (objectives). This backdrop sets the stage for our review, which addresses key questions surrounding the integration of SRL and AI.

1. Which stakeholder groups have predominantly been the focus of AI-supported SRL initiatives?
2. What prevailing theoretical frameworks underpin studies at the intersection of AI and SRL?
3. How has AI been implemented in SRL studies?
4. For what purposes has AI been deployed in support of SRL?

Methodology

A systematic mapping review was conducted using transparent and explicit methods (Gough et al., 2012; Zawacki-Richter et al., 2020), with the reporting here guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al., 2021) and the Quality of Evidence Synthesis Tool (QuEST; Bond et al., 2024). Unlike systematic reviews that synthesize evidence to understand a phenomenon's effect, mapping reviews categorize literature to identify research gaps (Grant & Booth, 2009; Sutton et al., 2019). All search strategy details, including the PRISMA checklist and appendices, are available on OSF.[1]

[1] https://osf.io/j92bu/?view_only=94e9f62043a741aa8130cfd40bb906a2

Table 1 Initial search string

Artificial Intelligence	"artificial intelligence" OR "machine intelligence" OR "intelligent support" OR "intelligent virtual reality" OR "chat bot*" OR "chatbot*" OR "machine learning" OR "automated tutor" OR "personal tutor*" OR "intelligent agent*" OR "expert system" OR "neural network" OR "natural language processing" OR "intelligent tutor*" OR "adaptive learning system*" OR "adaptive educational system*" OR "adaptive testing" OR "decision trees" OR "clustering" OR "adaptive system*" OR "AI-driven" OR "AI driven" OR "generative AI" OR "large language model*" OR "ChatGPT" OR "AI-supported regulat*"
AND	
SRL	"SRL" OR "self-regul*" OR "self regul*" OR "self-direct*" OR "self direct*"

Search strategy and study selection

Search string development

A search string was developed (see Table 1), which was adapted from a recent meta-review of AI in education research (Bond et al., 2024). It focused on identifying forms of AI and SRL, including terms related to self-directed learning. The decision not to use different permutations of SRL processes was made as it was reasoned that if a study was specifically focused on SRL, the term would be used in the title, abstract, or keywords. The search string also included AI terms related to generative AI, which differed from that used by Bond et al. (2024), including "large language model*" and "ChatGPT". Education related terms (e.g., "undergrad*") were also used during an initial scoping phase, but this excluded a lot of relevant studies, so the decision was made not to include them in the final search string.

Study identification

The initial search was conducted on 26 March 2024, with subsequent searches conducted until 1 May 2024 to ensure the inclusion of extant literature (see OSF for full search details). The platforms and databases searched were the Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and EBSCOHost (all databases), as these have been found suitable for evidence synthesis (Gusenbauer & Haddaway, 2020), alongside Google Scholar via Publish or Perish application (Harzing, 2007; limited to retrieving 1000 results). The journal Computers and Education: Artificial Intelligence was also manually searched via their website, as this was the journal where an influential AI and SRL paper had been published (Molenaar, 2022). The OpenAlex platform (Priem et al., 2022) was also later searched in May 2024 via evidence synthesis software EPPI Reviewer (Thomas et al., 2022), including bidirectional checking of citations and recommendations on identified items, after an initial portion of included items had been identified (see screening details in the next sub-section).

Initially, all platforms were searched for the time period 2014–2024, which resulted in over 5,000 items identified across the platforms after deduplication. However, given the scope of the project, the decision was made to limit the time period to 2018–2024 and to only include items that included the phrases SRL, self-regulated learning, or self-regulation in the title or abstract. This led to a decision to delete the initial searches, refine the search string (see Table 2), and search the same databases again (see OSF[2]). Following the new search, 4,702 items were finally identified, with 2,881 items then removed automatically within EPPI Reviewer (see Fig. 1).

Table 2 Final search string

Artificial intelligence	"artificial intelligence" OR "machine intelligence" OR "intelligent support" OR "intelligent virtual reality" OR "chat bot*" OR "chatbot*" OR "machine learning" OR "automated tutor" OR "personal tutor*" OR "intelligent agent*" OR "expert system" OR "neural network" OR "natural language processing" OR "intelligent tutor*" OR "adaptive learning system*" OR "adaptive educational system*" OR "adaptive testing" OR "decision trees" OR "clustering" OR "adaptive system*" OR "AI-driven" OR "AI driven" OR "generative AI" OR "large language model*" OR "ChatGPT" OR "AI-supported regulat*"
AND	
SRL	"self-regul*" OR "self regul*" OR "regulation of learning"

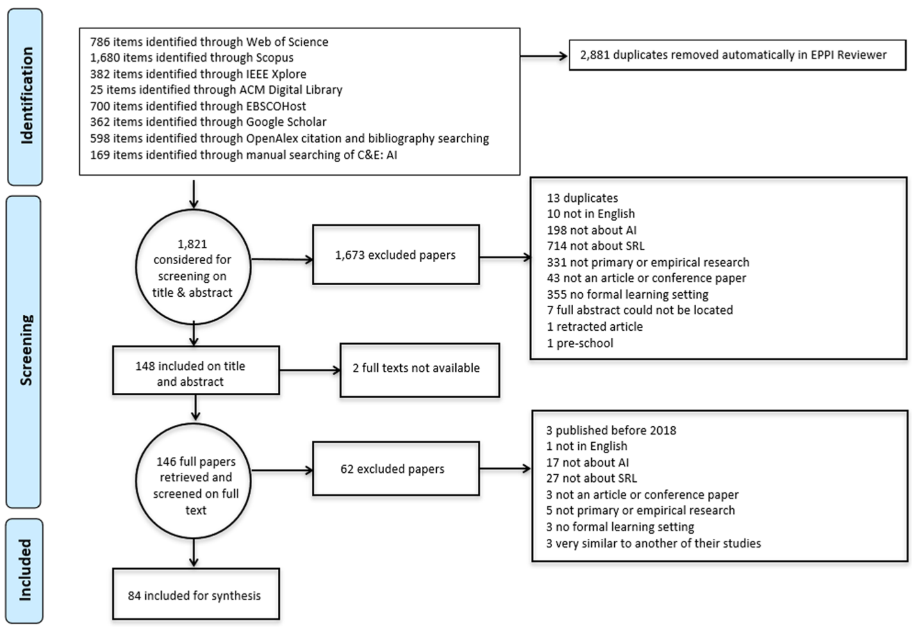

Fig. 1 PRISMA diagram of the search and screening strategy

Inclusion/exclusion criteria and screening

In total, 1,821 items remained to be screened on title and abstract, applying the inclusion and exclusion criteria (see Table 3). Studies were included if they were a primary empirical study published in English as a journal article or a conference paper after January 2018 and focusing on AI and SRL in a formal learning setting (primary/secondary school or higher education). To ensure inter-rater reliability between members of the research team, all authors blind-screened four rounds of 100 items, resulting in almost perfect agreement (Fleiss k = 0.80; Landis & Koch, 1977). The four authors involved in the screening process possess extensive expertise in technology-enhanced learning, with years of research and teaching experience in the field. Although some disagreements arose during the four rounds of screening, their collective expertise fostered consistency and a shared understanding of the criteria, which further enhanced the reliability of the coding process. After disagreements were reconciled, priority screening within

Table 3 Final inclusion/exclusion criteria

Inclusion	Exclusion
Focuses on AI and SRL	Published before 2018
Empirical study	Secondary research, editorials, conceptual
Journal articles & conference papers	Published in a language other than English
Published between 2018 and 2024	Not related to AI and SRL
Formal learning setting	Not K-12 or higher education
Published in English	SRL not mentioned in the title or abstract

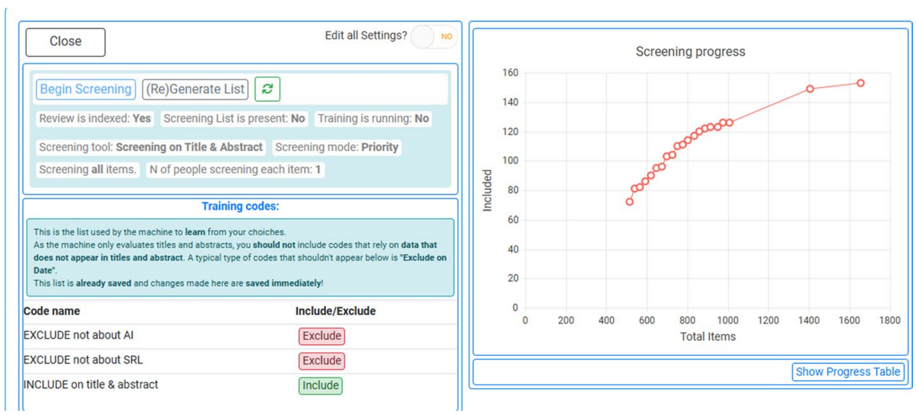

Fig. 2 Priority screening settings from within the EPPI Reviewer

EPPI Reviewer was activated and the remaining 1,421 items were screened in single screener mode. Priority screening uses machine learning that prioritizes the order that which items are presented to the reviewer, with those it identifies as being the most relevant presented first. In this case, the algorithm was trained using the exclusion codes 'EXCLUDE not about AI' and 'EXCLUDE not about SRL', as well as the include code 'INCLUDE on Title & Abstract' (see Fig. 2). After all items were screened on title and abstract, 146 full texts were retrieved to be screened on full text.

To continue ensuring inter-rater reliability at the screening on the full-text stage, 30 items were blind screened by three authors, achieving substantial agreement (Fleiss k = 0.73). The same three authors then screened the remaining items, identifying 84 for data extraction and synthesis.

Data extraction

The data extracted for this mapping review included publication and study characteristics (e.g., publication type and name, author countries, discipline, and country of study), the theoretical framework used (coded inductively), the role of AI in the study (e.g., intervention, analysis only), the type of AI used (e.g., intelligent tutoring system), the direct impact (cognitive, metacognitive or motivation), and the end outcome (e.g., academic achievement). The type of AI used was classified using the typology by Zawacki-Richter et al. (2020) and Bond et al. (2024). All data were extracted manually within EPPI Reviewer, with an initial five coded by all authors to ensure agreement and understanding of the coding scheme. The decision was then made for the second author to code general publication characteristics, RQ1 and RQ3, and the first author to code RQ2 and RQ4. Please see the OSF[2] for the full data extraction tool.

Data synthesis

As this is a mapping review, a narrative synthesis of the data was undertaken (Petticrew & Roberts, 2006), including a tabulation of the included studies (see Appendix 1), in order to provide an overview of the intersection of AI and SRL. Further tables are provided throughout the text, or included as appendices, accompanied by narrative descriptions. In order to provide further visual overviews, and to facilitate public access to the data beyond this article, interactive evidence and gap maps[3] were produced for each research question, using the EPPI Mapper application. An openly accessible web database of the included studies is also available,[4] created with EPPI Visualiser,[5] which allows users to view and interact with the data through frequency and crosstabulation charts, with direct links to articles and options to export the data.

Limitations

Although this review followed a rigorous and transparent process, there are some limitations that should be acknowledged. Firstly, the limited timeline and iterative nature of this project meant that a protocol was not pre-registered, however, the full search details are available on the OSF, as previously mentioned. The decision to limit the search string to include only permeations of 'self-regulation' may have excluded a number of studies, as might limiting the mention of self-regulation in the title or abstract. Other academic platforms could also have been searched, especially in light of the Global North geographical and linguistic bias in the strategy chosen (Stern & Kleijnen, 2020). Secondly, while our review aimed to capture a comprehensive set of studies at the intersection of AI and SRL, the decision to restrict inclusion to specific keywords in the title or abstract may have led to the exclusion of relevant work. In particular, studies that focus on SRL-related processes—such as goal-setting, self-monitoring, or mastery learning—or that use alternative terminology not captured by our search terms may have been inadvertently overlooked. Although our approach aligns with established previous literature synthesis protocols, it also introduces a methodological limitation. Future reviews may benefit from broader search strategies, such as keyword expansion or full-text searches, to provide a more inclusive representation of the literature. Thirdly, although systematic mapping reviews do not require a formal quality appraisal of included studies, studies that lacked a clear methodological description or that did not explicitly address SRL were excluded. We recommend that a full quality appraisal of studies should be conducted in any future full systematic reviews to strengthen the reliability and interpretive value of their findings.

[2] https://osf.io/j92bu/?view_only=94e9f62043a741aa8130cfd40bb906a2

[3] Available via the OSF link above.

[4] https://eppi.ioe.ac.uk/eppi-vis/login/open?webdbid=667

[5] https://eppi.ioe.ac.uk/cms/Default.aspx?tabid=3790

Findings

General publication characteristics

Interest in exploring the intersection of SRL and AI has grown substantially across the past three years, with 17 studies already published by the end of April 2024 (11 journal articles, and 6 conference papers). The 84 studies identified (see Appendix 1) have predominantly been published as journal articles (69%, N = 58) and are available as open access (74%, N = 62). Although authors were from 30 different countries (see Appendix 2), they hailed predominantly from North America (48%, N = 40), Asia (32%, N = 27) or Europe (30%, N = 25), with hardly any authors from the Middle East (N = 4), Oceania (N = 3), South America (N = 2) or Africa (N = 1).

In total, 71% of studies used quantitative approaches (N = 60), primarily collecting log data (N = 37), assessment results (N = 34), and questionnaire responses (N = 30). Some also used multimodal data (N = 11) such as eye trackers, facial recognition software, electrodermal activity bracelets, and heart rate monitors. Mixed methods studies (24%, N = 20) collected data through interviews (N = 10), reflections (N = 5), written artifacts (N = 4), and observations (N = 3). Only four studies used qualitative methods, exploring chatbots, ChatGPT's facilitation of self-regulation, and automated feedback tools. In total, 37% of studies collected data over two months or longer (N = 31), while 31% lasted less than one week (N = 26), and 24% did not report the study length (N = 20). Given the importance of ethical considerations with AI (Bond et al., 2024), the studies were also coded on whether participants had granted their consent, as well as the accessibility of study data. In total, 54% of studies confirmed participant consent (N = 45), while 39 did not mention it. Data was openly accessible in one study, available upon request in 22 studies, and not mentioned in 63% of studies (N = 53).

RQ1. Which stakeholder groups have predominantly been the focus of AI-supported SRL initiatives?

As expected, an overwhelming majority of AI-supported SRL initiatives have included students as participants (98%, N = 82) and, although the study by Hartley et al. (2024) did not have any participants, it explored how effective ChatGPT could be in supporting teenagers to learn how to program, thereby still supporting student learning. Indeed, only four studies featured educators, mostly to triangulate student opinions and researcher observations (e.g., Khidkikh et al., 2023). The mixed methods study by Kong and Yang (2024), however, explored the results of a 60-h professional development program for 31 in-service primary school educators in Hong Kong, which sought to measure their AI understanding and self-perceived competency, especially in regard to using generative AI. This was also the only study in the corpus that focused exclusively on the primary school level, with 20 studies focused on middle or high school students (Year 6—13), and 74% of studies exploring SRL in higher education (N = 62). Given that AI is currently in a transformative stage and considering that traditional human development involves an increasing capacity for self-regulation, we anticipate that research involving younger participants will expand as AI applications and adoption increase. Study participants were located within 20 different countries (see Appendix 4), with the majority of studies undertaken within North America (33%, N = 28) and Asia (25%, N = 21). 13 of the North American studies did not specify the exact country the students were located within, and 21% of studies did not specify which country their participants came from. Disciplines that were the most researched across all studies were Natural Sciences, Mathematics & Statistics (39%, N = 33), followed by IT / Computer Science (20%, N = 17), and Health & Welfare (17%, N = 14), with very little research undertaken with students in Education (10%) and Social Sciences (5%), and nine studies not specifying the disciplinary context (see Appendix 3). However, when cross-tabulated by study level, 31% of studies with postgraduate data included students within Education, and 70% of studies with data from Middle and High School students were from Natural Sciences, Mathematics & Statistics (N = 14).

RQ2. What prevailing theoretical frameworks underpin studies at the intersection of AI and SRL?

Our review revealed that a considerable number of studies (N = 33, 39%) did not clearly mention the underlying SRL theoretical framework for their study. From the remaining studies (N = 52, 61%), a large number of the studies built their framework on Zimmerman's model of SRL (2002) (N = 23, 27%; e.g., Nuankaew, 2020; Wu et al., 2024). This model adopts a socio-cognitive perspective of SRL (Panadero, 2017) and is structured around three phases: forethought, performance, and self-reflection. In the forethought phase, students engage in task analysis, goal setting, planning, and regulating their self-motivation and perceptions of their ability to achieve the expected outcomes. In the performance phase, students observe and monitor themselves while executing the task. This self-observation and self-monitoring help students maintain cognitive awareness of their learning process and sustain their motivation until the task is completed. In the self-reflection phase, students evaluate their performance and consider the reasons for their success or failure, which in turn affects their self-satisfaction and future approach to tasks (Panadero, 2017; Zimmerman, 2002).

The second most frequently used SRL model is based on the work of Winne and Hadwin (1998) (N = 9, 11%), such as the studies by Borchers et al. (2024), Taub et al. (2022). Winne and Hadwin's model (1998) comprises four phases: task definition, goal setting and planning, enacting study tactics and strategies, and metacognitively adapting studying. These phases occur within five facets of the task, known as COPES (Conditions, Operations, Products, Evaluations, and Standards). Heavily influenced by Information Processing theory, this model emphasizes the cognitive and metacognitive aspects of SRL (Greene & Azevedo, 2007; Panadero, 2017).

Another identified theory is Co- and Socially Shared Regulation of Learning (SSRL), proposed by scholars such as Hadwin and Järvelä (Hadwin et al., 2011) (N = 4, 5%; e.g., Suraworachet et al., 2024). While this model is strongly influenced by Winne and Hadwin's model of SRL (1998), it addresses the regulation of learning at a group level within collaborative learning contexts (Järvelä & Hadwin, 2013). According to this model, SRL occurs at three levels. At the first level, students regulate cognitive, metacognitive, motivational, emotional, and behavioural aspects of their learning processes. Second, at the co-regulated level, regulation occurs through interaction between two students, where one student's regulatory processes support or influence the other's. Third, at the socially shared regulated level, regulation is collectively managed through collaborative interactions among group members working towards common learning goals (Panadero, 2017).

Another model that grounded three studies (4%) was Pintrich's (2000) model of SRL (Drzyzga et al., 2023; Hartley et al., 2024; Ye, 2022). Pintrich's (2000) SRL model identifies four key phases: (1) Forethought, planning, and activation; (2) Monitoring; (3) Control; and (4) Reaction and reflection. These phases intersect with four areas of regulation: cognition, motivation/affect, behavior, and context. Together, these phases and areas offer a holistic view of SRL processes such as goal setting, activation of prior knowledge, cognitive judgment, and evaluation of tasks (Panadero, 2017; Pintrich, 2000).

We also identified that several studies (N = 6, 7%) utilized different SRL models. Miller and Bernacki (2019) grounded their study in Butler and Cartier's model of SRL (2018), which situates SRL within the context of individual-context interactions, environmental influences, students' ongoing appraisal of the environment, and their experiences of motivation, emotion, and affect. Wiedbusch et al. (2023) employed Efklides's model of SRL (2011), which includes two levels: the person level, characterizing general SRL functions such as self-concepts and motivation, and the task x person level, defining SRL based on the interaction between tasks and students, including self-monitoring and self-observation during performance (Efklides, 2011; Panadero, 2017). Dever et al. (2022) adopted Kramarski and Heaysman's model of educators' triple SRL-SRT processes (2021), which describes how educators activate students' SRL. Watts et al. (2023) built their study on Nicol and Macfarlane-Dick's Feedback-SRL model (2006), which proposes that self-regulated processes mediate how students use domain knowledge to set goals and develop strategies for achieving internal learning outcomes. Sáiz-Manzanares et al. (2023) focused on the metacognitive aspect of SRL, basing their research on Román and Poggioli's (2013) classification of metacognitive strategies (self-knowledge, self-planning, and self-assessment). Du (2021) used the SMART framework (specific, measurable, attainable, relevant, and timely) to guide students in goal-setting (Doran, 1981).

Another notable finding is that several studies adopted an integrative approach to SRL, combining concepts from various models (N = 6, 7%). For instance, Nuankaew (2022) utilized two SRL theories: Bandura's conceptualization, which includes self-observation, the judgmental process, and self-reaction (Bussey & Bandura, 1999), and Zimmerman's SRL model (2002). Similarly, Zheng (2019) examined SRL at both the individual level, incorporating ideas from Pintrich (1995, 2000), Winne and Hadwin (1998), and Zimmerman (2002), and at the group level, considering SSRL as described by Hadwin and Järvelä (Hadwin et al., 2011) (see Fig. 3).

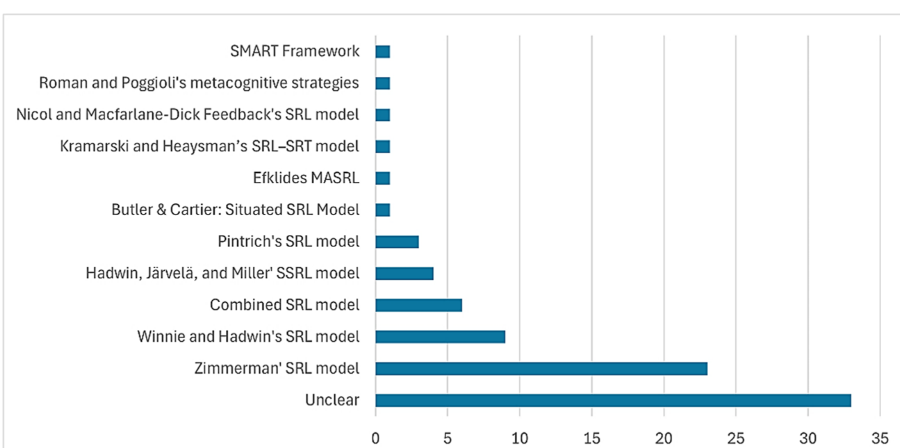

Fig. 3 Predominant theoretical frameworks underpinning studies at the intersection of AI and SRL

RQ3. How has AI been implemented in SRL studies?

AI was implemented primarily as an intervention to support student learning (75%, N = 63), such as implementing an intelligent tutoring system (e.g., Cerezo et al., 2020), with six of these studies also using it to perform further clustering or analysis to profile student categories (7%). For example, Li et al. (2023) explored how machine learning could be used to detect goal-setting and planning activities within think-aloud transcripts from medical students who used an intelligent tutoring system to diagnose virtual patients. Ten studies also explored student acceptance of or their attitude towards using chatbots (e.g., Sáiz-Manzanares et al., 2023), ChatGPT (e.g., Ng et al., 2024), adaptive systems (e.g., Harati et al., 2021), and dashboards (e.g., Üstün et al., 2023).

The studies were further classified using the framework of Bond et al. (2024), adapted from Zawacki-Richter et al. (2020), which categorizes AI use into four overarching categories: profiling and prediction, intelligent tutoring systems, adaptive systems and personalization, and assessment and evaluation (see Fig. 4). The most frequent implementation of AI in SRL studies has been adaptive systems and personalization (41%, N = 35), followed closely by profiling and prediction (38%, N = 32), 33% (N = 28) explored intelligent tutoring systems, and only three studies explicitly focused on assessment and evaluation.

Adaptive systems and personalization

Articles using adaptive systems and personalization were classified into five sub-categories: chatbots/GenAI/NLP (N = 15), dashboards/automatic feedback (N = 11), facial/mood recognition (N = 5), recommender systems (N = 4) and writing support systems (N = 3).

Chatbots have been used within a range of disciplines in the form of commercial applications (e.g., Xia et al., 2023), bespoke chatbots developed for specific courses (e.g., Sáiz-Manzanares et al., 2023), or using the ChatGPT interface or API. Dahri et al. (2024) conducted a mixed-methods study where pre-service educators used ChatGPT to undertake SRL-based lesson plan creation tasks, which were then evaluated, alongside using the Technology Acceptance Model to assess the pre-service educators' attitudes towards using generative AI. The impact of ChatGPT-based chatbots on SRL was explored within high school (Ng et al., 2024) and undergraduate (Lee et al., 2024) science

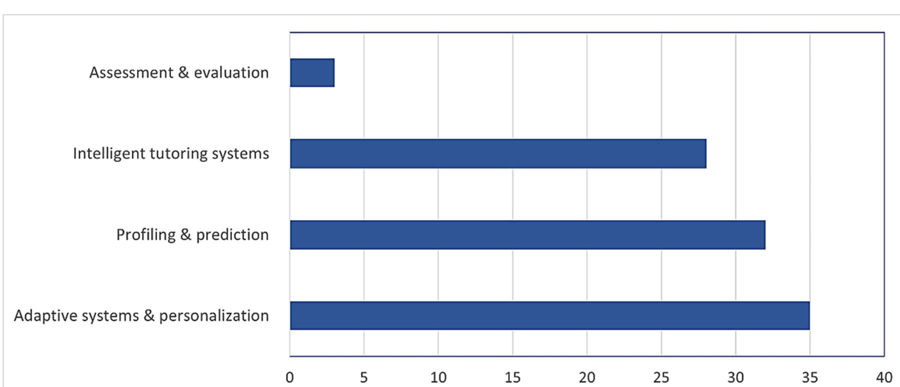

Fig. 4 Categorization of AI implementation in studies at the intersection of AI and SRL

education, as well as a high school Maths class in a two-week quasi-experiment (Wu et al., 2024). In a slightly different application of generative AI, Suraworachet et al. (2024) used the ChatGPT API as one of three models evaluated for predicting SRL, finding that the LLM and supervised machine learning both showed equivalently high performance across most tasks, although the LLM could not identify metacognitive challenges. Unfortunately, there were two studies that did not provide any information about the chatbot or how it was implemented (Sandoval Peña et al., 2023), which limits its generalizability.

Dashboards were also a popular form of adaptive system used, although these studies predominantly focused on their use within Computer Science (N = 8). For example, Afzaal et al. (2024) explored whether a dashboard that showed students' predicted final exam performance and highlighted areas of learning improvement would affect their academic performance and support SRL. Likewise, Drzyzga et al. (2023) sought to understand how dashboards could be better structured, so as to promote SRL and motivate students to use it, with Üstün et al. (2023) finding that consideration needs to be given to the stress and anxiety that constant feedback and monitoring can have on students.

Profiling and prediction

The majority of studies classified in this category used AI to profile students' SRL behaviors by using clustering algorithms (e.g., Song et al., 2024), including exploring the use of machine learning to predict students' regulatory patterns in collaborative learning tasks (Järvelä et al. 2023b; Vuorenmaa et al., 2023). However, only eight studies explored profiling and prediction within primary, middle, or high schools, with six of these focused on use cases within STEM subjects. In a study of 144 high school and college students, Zheng et al. (2019) developed a semiautomated workflow to identify SRL and SSRL patterns in chat messages. They first manually coded 886 chat messages and used it to train four machine learning algorithms (random forest, SVM, decision tree, and naïve Bayes), evaluating their performance using a tenfold cross-validation method. They then applied the model with the best generalization and performance (decision tree) to the rest of the chat messages to automatically detect SRL and SSRL.

Studies also used AI to predict academic performance and to help identify those students who were at risk of dropping out. For example, Cogliano et al. (2022) developed a model that could accurately identify students who would earn a C- or less using pretest scores and event data that were available by the second week of a course, three weeks before their first exam. This model was then used on a new cohort of students to predict students who were in the at-risk risk group and provided with a training intervention, which improved their learning performance. Similarly, Tu et al. (2023) developed and validated a model using PLS-SEM and machine learning to help predict student burnout in China, finding that BayesNet outperformed other classifiers in predicting both perceived social support and burnout.

Intelligent tutoring systems

A range of intelligent tutoring systems (ITS) has been used to explore SRL (see Appendix 1), including 11 studies focused on MetaTutor, an ITS that teaches students about the human circulatory system (e.g., Wiedbusch et al., 2023), and five studies considered

SRL phases and student confidence in virtual patient diagnosis in BioWorld (e.g., Huang et al., 2023a). However, 61% (N = 17) of ITS studies have been undertaken across two weeks or less, with only four studies identified that explored SRL across two months or longer. For example, Harati et al. (2021) investigated whether students' scores changed across eight SRL variables as a result of using ALEKS as the learning system during a semester Introduction to Chemistry course, as well as seeking to understand the students' perceptions towards using the system. ALEKS prompts students periodically to undertake progress checks to monitor their knowledge and retention, which then helps the system know when to adapt a learning path; a common reason given across the studies as to why ITS was chosen as a means to explore SRL. Ferreira da Rocha et al. (2024) also explored the effect of gamification on SRL, where users can spend points to buy solutions to problems, although no significant differences were found.

Assessment and evaluation

Three studies explored the use of systems that use automated grading or writing evaluation. In Ortega-Ochoa et al.'s (2024) quasi-experimental study of an empathic chatbot (DSLab-Bot) in online learning, student assignments were automatically evaluated, and the dashboard used in Sun et al.'s study (2023) evaluated learning performance and mastery levels over time. Watts et al. (2023) developed and tested an automated formative feedback tool with Chemistry students, whose design was based on SRL theory.

RQ4. For what purposes has AI been deployed in support of SRL?

Our review showed that the use of AI in supporting SRL has extended beyond just focusing on and supporting SRL itself; it has also aimed to enhance various educational and learning activities as end outcomes. Therefore, based on these diverse findings, we categorized AI's impact on SRL into two main groups: direct *impacts* on SRL and end outcomes resulting from AI's influence on SRL.

Direct impacts on SRL

To present the results of the direct impacts of AI on SRL, we organized them into three primary aspects: Cognition (including encoding, organization, elaboration, and inferencing), Metacognition (covering knowledge of cognition such as declarative, procedural, and conditional, as well as regulation of cognition including planning, monitoring, and evaluation), and Motivation (encompassing aspects like self-efficacy, attributions, goal orientation, and intrinsic motivation) (Schraw et al., 2006). Out of the 84 studies reviewed, 51 investigated the impact of AI on the cognitive aspects of SRL. Within this subset, AI's impact on the metacognitive aspect of SRL emerged as the primary area of focus in 73 studies. In contrast, AI's impact on the motivational aspect of SRL was examined only in 20 studies of the reviewed pool. This pattern indicates a strong emphasis on exploring how AI affects learners' metacognitive and cognitive processes, with relatively less attention given to the role of AI in influencing motivation (see Fig. 5).

Among the reviewed studies, some focused on the impact of AI on only one aspect of SRL. For instance, Cogliano et al. (2022) and Drzyzga et al. (2023) examined the cognitive aspect, Dahri et al. (2024) and Ferreira da Rocha et al. (2024) explored

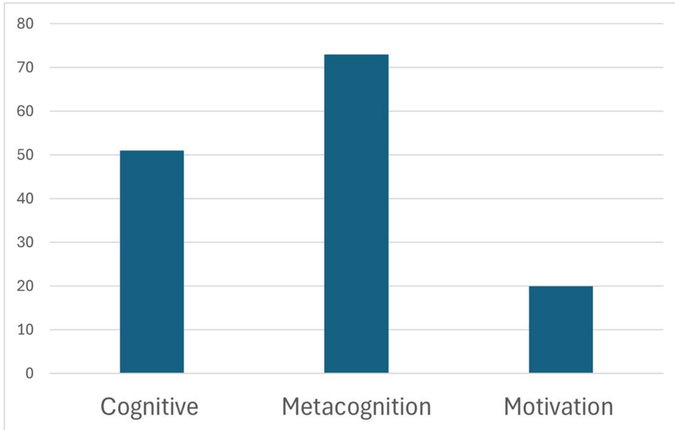

Fig. 5 Categorization of the direct impact of AI use in supporting SRL in studies at the intersection of AI and SRL

the metacognitive aspect, and Bouchet et al. (2018) concentrated on the motivational aspect. Additionally, some studies addressed two or all three aspects of SRL. For example, Afzaal et al. (2021) and Borchers et al. (2024) focused on the cognitive and metacognitive aspects, while Harati et al. (2021) and Järvelä et al. (2023a, 2023b) investigated the impact of AI on all three aspects.

The impact of AI on various aspects of SRL exhibits considerable diversity across different studies. For example, Afzaal et al. (2024) explored how AI, through intelligent automatic action recommendation systems, can provide actionable insights to support students' SRL activities. In contrast, other research, such as Burman et al. (2020), employed AI techniques like educational data mining and machine learning to categorize students' self-regulation strategies and analyze their correlation with academic performance. Further, studies by Chen and Li (2021) utilized hierarchical cluster analysis to profile students' behaviors based on their SRL activities, aiming to better target their SRL needs and offer tailored support. Another innovative approach was taken by Cloude et al. (2020), who used AI to capture and analyze students' emotions. This analysis provided valuable implications for designing affect-sensitive Intelligent Tutoring Systems that enhance emotion regulation. Similarly, Domínguez et al. (2021) employed process mining to explore how students self-regulate during the learning processes. Another adoption of AI in SRL is demonstrated by Cogliano et al. (2022), who focused on AI's ability to predict students' future SRL strategies, to use AI for educational support. These diverse applications of AI illustrate its multifaceted impact on SRL, highlighting its role in providing recommendations, categorizing SRL strategies, profiling SRL behaviors, analyzing emotions, exploring learning processes, and predicting SRL performance.

End outcomes

In reviewing 84 studies on the use of AI to support SRL, we identified a range of educational and learning activities that were positively impacted. The most frequently reported outcome was an improvement in academic performance, cited in 40 of the reviewed studies (48%), indicating that AI enhances students' academic achievements in different contexts such as language learning and writing skills (Wei, 2023) or mathematics (Liu et al., 2024) by supporting their SRL processes. AI interventions were also found to impact student motivation in 12 studies (14%) by supporting their SRL activities. The impact of AI on student motivation encompasses various dimensions: it increases motivation for learning (Wang et al., 2024), explores factors influencing student motivation to use AI for SRL activities (Dahri et al., 2024), and examines the effects of different motivational needs such as autonomy, relatedness, and competence on SRL (Xia et al., 2023).

Additionally, 10 studies (12%) reported increased student engagement due to AI support, demonstrating that AI tools can make learning more interactive and captivating for students. Similar to its impact on motivation, AI's influence on engagement is diverse, encompassing the use of AI to explore students' cognitive and behavioral engagement (Huang et al., 2023a), their engagement levels in SRL activities (Raković et al., 2024), and to cluster students according to their engagement patterns (Rienties et al., 2019). The impact of AI on students' emotional states was observed in nine studies (11%), highlighting AI's potential to address emotional aspects of learning. AI's capacity to influence student emotions spans various dimensions, from exploring emotional states (e.g., confusion, boredom, frustration, shame, etc.) during SRL activities (Bouchet et al., 2018), to measuring affective learning (interest, focus, energy, tension, and valence) (Martens et al., 2020), to predicting the relationship between emotions (surprise, curiosity, enjoyment, boredom, etc.) and the use of SRL strategies (Rienties et al., 2019).

It was also found that seven studies (8%) highlighted the role of AI in facilitating collaborative learning, enhancing group activities and peer interactions, leading to improved learning outcomes within a socially-shared regulation context (Järvelä et al. 2023c; Suraworachet et al., 2024). Reasoning skills were improved in five studies (6%), showing that AI can aid in developing critical thinking and logical reasoning abilities (Ortega-Ochoa et al., 2024). In addition, four studies (5%) discussed the use of AI for creating student learning behavior profiles, which help tailor educational experiences to individual needs (Song et al., 2024). Furthermore, in four studies (5%), it was reported that the use of AL led to increased student satisfaction with the learning process (Nuankaew, 2020; Xia et al., 2023).

In addition, AI tools helped reduce anxiety in three studies (4%), suggesting that AI can provide support to alleviate stress and anxiety in educational settings (Jebur et al., 2022; Liao et al., 2024; Ng et al., 2024). Social interaction was enhanced in three studies (4%), highlighting AI's role in fostering better communication and collaboration among students (Vuorenmaa et al., 2023; Wei, 2023; Zhang et al., 2022b). Also, two studies (2%) reported the role of AI in autonomous learning, where students became more independent and self-directed learners (Pierrot et al., 2021; Sandoval Peña et al., 2023)., AI's role in facilitating knowledge construction was noted in two studies (2%), aiding students in building and organizing knowledge (Lee et al., 2024; Wu et al., 2024). In addition, AI interventions improved problem-solving skills in two studies (2%), helping students develop effective strategies to tackle challenges (Nagashima et al., 2022; Zhang et al., 2022b). Two studies (2%) reported enhancements in reading performance, indicating AI's potential to support reading literacy and comprehension skills (Hsu et al., 2022; Serrano et al., 2018).

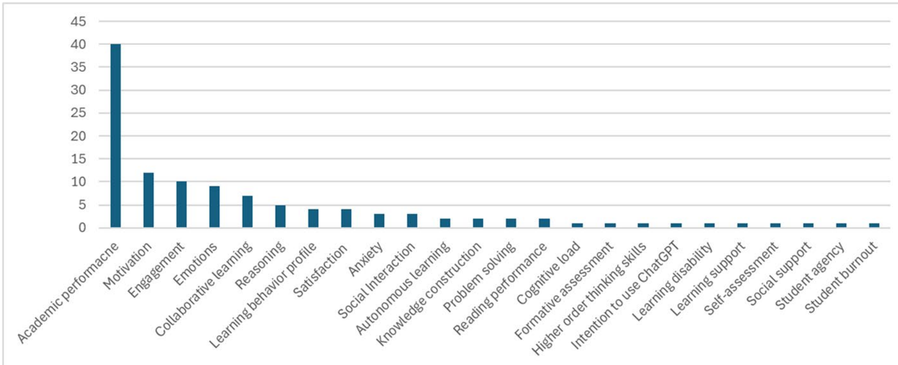

Fig. 6 Categorization of the end outcomes of AI use in supporting SRL in studies at the intersection of AI and SRL

AI support for students with learning disabilities was highlighted in one study (Cerezo et al., 2020), showing its potential to provide inclusive education, and one study (1%) emphasized AI's role in providing learning support, enhancing the overall learning experience (Hartley et al., 2024). AI's role in providing social support was noted in one study (Tu et al., 2023), aiding in the creation of a supportive learning environment. One study (Darvishi et al., 2024) discussed the role of AI in student agency and taking control of their learning, and AI interventions helped address student burnout in one study (Tu et al., 2023), suggesting AI's potential in promoting student well-being (see Fig. 6).

Discussion

In this study, we systematically synthesized and mapped the intersection of AI and SRL, building upon the framework by Chatti et al. (2012). Below, we discuss the general findings and the results for each research question.

Discussion on the general findings

The substantial growth of AI-SRL publications in the past two years highlights the growing importance of integrating AI into SRL research. However, most studies are concentrated in North America, Asia, and Europe, with limited representation from the Middle East, Oceania, South America, and Africa. This imbalance may be due to funding limitations and barriers to international collaboration, suggesting a need for more global participation to bring diverse perspectives to the field. This could foster a more comprehensive understanding of how AI can support SRL across different educational contexts and cultural settings. The predominance of quantitative approaches in AI-SRL research using multimodal data, log data, and assessment data followed by mixed methods highlights a trend towards a hybrid approach, empirical rigor, and measurable outcomes in this field. However, qualitative methods are notably underrepresented. This gap limits our understanding of the nuanced experiences, perceptions, and contextual factors influencing AI's effectiveness in SRL.

Most studies are short-term, with only about one-third extending beyond two months. Longitudinal research is needed to assess the long-term impacts and effectiveness of AI on SRL, which is crucial for understanding sustained changes and informing policy decisions. In addition, the longitudinal perspective is crucial for evaluating the effectiveness, durability, and scalability of AI-driven approaches in enhancing SRL activities. The findings concerning ethical considerations and data accessibility in AI-SRL research emphasize the critical need for adherence to ethical guidelines, especially regarding participant consent and data transparency (Nguyen et al., 2023; Noroozi et al., 2024). Improving transparency and ethical practices is essential for ensuring trust and integrity in AI-SRL research (Bond et al., 2024).

Discussion on the findings of RQ1: stakeholders

In AI-SRL research, students are overwhelmingly the primary focus, with most studies examining how AI supports students' SRL (e.g., Afzaal et al., 2024; Cogliano et al., 2022). This highlights a significant gap in overlooking educators, who are crucial in implementing SRL strategies. Educators play a critical role in implementing and facilitating SRL strategies in the classroom, and their insights and experiences are vital for the effective integration of AI tools in educational settings to support students' SRL activities (Phillips et al., 2022).

Within the group of students as the main target group, there is a lack of research on AI's role in supporting SRL for primary school students, pointing to a need for targeted studies that address the specific needs of this educational level. AI tools should be effectively integrated to support SRL at the primary education level, as this stage is crucial for developing foundational SRL skills. Research indicates that AI could play a significant role in this developmental phase (McClelland & Cameron, 2012). On the other hand, the predominance of AI-SRL research in higher education contexts may be due to the higher autonomy and complexity of SRL processes at this level (Cassidy, 2011), which align well with the advanced capabilities of AI tools.

Discussion on the findings of RQ2: underlying theory

A significant number of studies did not explicitly mention their theoretical framework, highlighting a need for greater transparency and rigor in in theoretical grounding within AI-SRL research. Establishing robust theoretical foundations is crucial for making research findings interpretable, comparable, and useful for designing effective AI interventions in SRL (Bond et al., 2024). Aligning AI tools with established SRL theories enhances the credibility and applicability of results for educators (Kitto et al., 2023).

Among studies that did specify a theoretical framework, Zimmerman's SRL model (2002) was the most frequently used, reflecting this model's longstanding prominence in the literature. Initially introduced by Zimmerman (1986), this model represents one of the pioneering efforts to define and conceptualize SRL. It offers a comprehensive cyclical framework that illuminates the iterative nature of SRL processes (Zimmerman, 2002). Winne and Hadwin's (1998) SRL model was also widely adopted, likely due to its focus on metacognition, which aligns with the prevalent focus on this aspect in AI-SRL research. SSRL (Hadwin et al., 2011) was noted for its emphasis on co-regulation and collaborative learning, relevant for AI applications that support social learning. Pintrich's (2000) SRL model was used in several studies, likely due to its emphasis on motivation, which makes it particularly relevant for exploring AI's impact on the motivational aspects of SRL.

The review also found a trend towards integrating multiple SRL models. This approach provides a more nuanced understanding that single-theory approaches might overlook.

This approach is particularly useful in addressing the diverse contexts in which SRL occurs. For instance, Bandura's focus on self-efficacy and social learning complements Zimmerman's cyclical model of SRL (2002), while the inclusion of SSRL accounts for collaborative learning environments (Hadwin et al., 2011). This allows researchers to design AI interventions that are adaptable to various educational settings, from individual learning tasks to group-based projects. However, on the other hand, it necessitates careful consideration to maintain theoretical coherence and effective implementation.

Discussion on the findings of RQ3: AI implementation

AI was implemented primarily as an intervention to support student learning (e.g., Cerezo et al., 2020). This focus on AI as an intervention likely stems from its effectiveness in providing personalized learning experiences, immediate feedback, and adaptive learning paths, which contribute to its widespread adoption (Afzaal et al., 2023). The review identified four categories of AI implementation in supporting SRL including adaptive systems and personalization, profiling and prediction, intelligent tutoring systems (ITS), and assessment and evaluation.

Adaptive systems and personalization emerged as the most researched AI implementation, reflecting the growing focus on tailored educational experiences. These systems, including chatbots, dashboards, and other personalized feedback mechanisms, are designed to address individual student needs, making learning more effective and engaging by providing real-time, personalized feedback which is crucial for fostering SRL (Afzaal et al., 2024; Pardo et al., 2019). For example, personalized and adaptive feedback can help students identify their strengths and weaknesses and adjust their learning strategies accordingly (Moon et al., 2024). While this feedback helps students adjust their learning strategies, constant monitoring might also increase stress and anxiety (Üstün et al., 2023). This highlights the need for careful consideration of the psychological effects of these technologies to ensure they support student well-being alongside academic performance.

The review found that most studies on profiling and prediction used AI to analyze SRL behaviors through clustering algorithms and to predict academic performance and dropout risks (e.g., Cogliano et al., 2022; Song et al., 2024). AI's role in profiling and prediction offers actionable insights that enhance learning regulation and enable targeted interventions to improve academic outcomes (Afzaal et al., 2021; Lee & Chung, 2019). By identifying specific patterns in SRL and academic performance, educators can offer personalized support to students who might otherwise be overlooked (Afzaal et al., 2021).

Findings on ITS show varied applications in studying SRL. Most ITS studies were short-term, lasting two weeks or less, with only four extending beyond two months. This may reflect the exploratory nature of early research, where shorter studies quickly assess effectiveness before longer investigations. ITS like MetaTutor (Cloude et al., 2020) and BioWorld (Huang et al., 2023a) excel in teaching complex subjects through interactive, individualized experiences, particularly in fields like medical education. ITS can provide highly interactive and individualized learning experiences, which are particularly useful in fields that require deep understanding and practical application, such as medical education (Mousavinasab et al., 2021).

The detailed feedback and adaptive learning paths inherent in ITS like ALEKS demonstrate how these systems can support SRL by helping students identify knowledge gaps and adjust their learning strategies accordingly. The use of gamification in ITS, aimed at boosting engagement and motivation (Ferreira da Rocha et al., 2024), suggests that its effectiveness depends on thoughtful integration rather than just the presence of gamified elements. Further research is needed to optimize gamification in ITS for better SRL support and improved learning outcomes.

Few AI-SRL studies have focused on AI for assessment and evaluation, such as automated grading and writing evaluation (Ortega-Ochoa et al., 2024). The lower focus on assessment and evaluation might suggest that this area is more challenging to address with AI, or perhaps less explored due to the complexity of developing reliable automated grading systems. Ensuring fairness, accuracy, and transparency in AI-driven assessment tools is critical, and these challenges might contribute to the limited number of studies in this category (Ferrara & Qunbar, 2022). Despite this, automated grading systems represent a shift toward more efficient and scalable assessments, saving educators time and providing immediate feedback that supports SRL (Banihashem et al., 2024).

Discussion on the findings of RQ4: AI application

AI-SRL research predominantly focuses on enhancing cognitive and metacognitive processes. It supports students in processing and organizing information, which are crucial for learning, and helps them structure and connect knowledge for deeper learning. Additionally, AI aids metacognition by providing feedback, helping with study planning, and assessing progress, thereby fostering self-awareness and strategic learning (Afzaal et al., 2024; Dahri et al., 2024). The limited focus on motivation reveals a research gap. While cognitive and metacognitive functions are crucial, motivation is also equally important. Sstudents' confidence in their ability to perform a task and their belief in themselves play a critical role in the successful completion of learning tasks (Pintrich, 1995, 2000). Future research should explore how AI can enhance motivational aspects of SRL, such as personalizing motivational strategies based on individual needs and profiles.

While motivational aspects of SRL were in general less explored, the observation that some studies addressed multiple SRL aspects (Harati et al., 2021; Kooken et al., 2021), demonstrates AI's comprehensive potential in fostering an integrated SRL environment. AI's diverse applications—such as SRL recommendations, profiling, measurement, process mining, and prediction—demonstrate its role in personalizing learning and enhancing SRL. For instance, SRL recommendations can provide tailored advice to students on how to improve their learning strategies, while profiling and measurement can help in understanding and tracking individual learning behaviors.

AI-SRL research shows broad positive impacts on education, with improved academic performance being the most frequent outcome. AI enhances achievements in subjects like language, writing (Wei, 2023), and math (Liu et al., 2024) by supporting SRL. It also boosts student engagement, motivation, and emotional experiences, making learning more interactive and responsive (Bouchet et al., 2018; Raković et al., 2024; Xia et al., 2023). Improvements in collaborating learning resulting in the use of AI indicate that AI can facilitate more effective group work and peer learning, potentially leading to better collective learning experiences and outcomes (Järvelä et al. 2023b, 2023c). AI has also shown potential to support reasoning skills (Huang et al., 2023a). This suggests that AI tools can be instrumental in fostering higher-order cognitive skills that are essential for complex problem-solving and decision-making. AI's positive impact on reducing anxiety (Jebur et al., 2022), improving social interaction (Wei, 2023), and enhancing autonomous learning (Sandoval Peña et al., 2023) collectively illustrate the diverse and impactful ways AI is being utilized to support and enhance various educational and learning activities,

Implications for research

The implications for future research in the field of AI for SRL are multifaceted and necessitate the need for a more inclusive and comprehensive approach. There is a need for studies from the Global South (e.g., the Middle East, Oceania, South America) to address diverse educational contexts. Expanding research to include primary and secondary education will help tailor AI-supported SRL to younger students. Qualitative and mixed methods can provide deeper insights, while longitudinal studies are essential for understanding long-term effects. Ethical considerations, such as explicit consent and data transparency, must be prioritized to build trust and foster further research collaborations.

Further exploration of automated writing systems and feedback mechanisms could significantly enhance SRL by offering personalized, timely support and improving learning outcomes. This is highly important, especially considering the forms of human-AI collaboration in providing feedback for enhancing SRL activities (Banihashem et al., 2025). In addition, more research is needed on AI for assessment and evaluation in SRL.

Future research should also focus on clearly articulating the theoretical basis of AI-supported SRL interventions to ensure coherence and enhance the validity of the findings and also to explore and refine integrative frameworks, leveraging the strengths of various SRL theories and models to support the diverse and complex nature of SRL in the age of AI.

Additionally, there is a pressing need to expand AI-SRL research that includes educators as primary participants. Moreover, we advocate for evaluating the positive and negative effects of AI-SRL interventions on both individual and group learning levels, including reporting effect sizes. Finally, we emphasize the importance of exploring the motivational aspects of SRL as a critical focus for future research.

Implications for practice

Given the dominance of studies from North America, Asia, and Europe, it is essential for practitioners in underrepresented regions to contribute and adapt these insights to their local contexts. Geographic diversity is vital for creating culturally sensitive and globally applicable AI tools. Due to the short duration of many AI-SRL studies, educators should interpret findings cautiously and implement AI interventions over longer periods to assess their effectiveness and make necessary adjustments. Additionally, practitioners must uphold rigorous ethical standards, including explicit consent and transparency, to build trust and support further collaboration in the educational community.

Future practice should involve educators more actively in developing and refining AI-supported SRL interventions to ensure alignment with classroom dynamics and pedagogical goals. Connecting AI tools to established SRL models can enhance trust and guide effective application. AI's role in adaptive learning offers opportunities for tools like chatbots and dashboards to address diverse learning needs (Debets et al., 2025). Profiling and predicting students' SRL behaviors can help identify at-risk students and forecast academic outcomes for timely interventions. Despite limited use in assessment, AI shows potential for automated grading, which educators should consider exploring.

The focus on AI's cognitive and metacognitive impacts highlights its potential to improve how students manage their learning. Educators should integrate AI tools to enhance students' cognitive and metacognitive regulation of learning and consider AI's broader educational benefits, using these tools to support diverse learning outcomes.

Conclusion

This systematic review represents one of the initial efforts to map the intersection of AI and SRL research. It has expanded our understanding of the current state of AI-SRL research by examining trends over the past six years, including study levels, participant demographics, and geographical distribution. Additionally, this study has added value to the existing body of AI-SRL literature by clarifying key targeted stakeholders, elucidating the underlying SRL theories, and detailing the variations in AI implementation for SRL. We have also highlighted the direct impacts of AI on SRL processes and the broader educational outcomes resulting from AI integration. By identifying both research and practical gaps within the AI-SRL nexus, this review provides a holistic picture that can guide future research directions and inform practice. The insights garnered from this review are crucial for advancing the effective application of AI in supporting SRL and optimizing educational outcomes.

Appendix 1: List of studies in the corpus (n = 84)

Adaptive systems and personalisation studies (n = 35)

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Afzaal et al	2021		Students & Teachers	157 +	PG	Sweden	MM	?	Support learning Support teaching	Dashboard	X	X		Achievement, Motivation
Afzaal et al	2023		Students	446 + 356	UG	Sweden	MM	Zimmermann	Support learning	Dashboard	X	X		Achievement
Chakraborty et al	2021		Students	10,958	MS/HS	USA	Quanti	?	Support learning	Recommender	X			Achievement
Dahri et al	2024		Students	300	UG	Malaysia	MM	Zimmermann	Support learning AI attitude	ChatGPT		X		Intention to use AI, Motivation
Darvishi et al	2024		Students	1,625	UG	?	Quanti	?	Support learning	Writing support NLP/LLM		X		Achievement, student agency
Domínguez et al	2021	–	Students	382	HE	?	Quanti	Combination	Support learning	Automatic feedback		X		Self-assessment, formative assessment, engagement
Drzyzga et al	2023		Students	10	UG	?	MM	Pintrich	Support learning	Dashboard	X			Cognitive load

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Du et al	2021	–	Students	18	HE	China	Quali	SMART	Support learning AI attitude	Chatbot		X		Design of chatbots
Durall et al	2022		Students & Teachers	12 + 7	UG	Spain	Quali	Zimmermann	Support learning AI attitude	Chatbot	X	X		Design of chatbots
Gumaa et al	2024		Students	30	UG	Egypt	Quanti	Zimmermann	Support learning AI attitude	Chatbot		X		Satisfaction
Hartley et al	2024		–	–	–	–	Quali	Pintrich	Support learning Support teaching	ChatGPT	X	X		Learning support
Järvelä et al	2023		Students	82	HS	?	Quanti	SSRL	Support learning	Mood detection	X	X	X	Collaborative learning
Järvelä, Nguyen et al	2023		Students	94	HS	?	Quanti	SSRL	Analysis	Mood detection	X	X	X	Collaborative learning
Jebur et al	2022		Students	260	UG	?	Quanti	Zimmermann	Support learning	Recommender, Automatic feedback		X		Reduced anxiety

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Kong & Yang	2024	–	Teachers	31	PS	China	MM	Zimmermann	Support learning Support teaching	ChatGPT		X		Achievement
Lee et al	2024		Students	61	UG	Taiwan	Quanti	Zimmermann	Support learning	ChatGPT	X	X	X	HOTS, knowledge construction
Liao et al	2024	–	Students	125	HS	China	Quanti	?	Support learning	Dashboard	X	X	X	Achievement, motivation, anxiety

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Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Ng et al	2024	a	Students	74	HS	China	MM	Zimmermann	Support learning AI attitude	ChatGPT	X	X	X	Achievement, reduced anxiety, motivation
Ortega-Orchoa et al	2024	a	Students	196	HE	Spain	Quanti	?	Support learning	Chatbot	X	X	X	Achievement, reasoning, motivation
Phodong et al	2022	a	Students	31	UG	Thailand	Quanti	Zimmermann	Support learning	Writing support NLP		X		Achievement
Pierrot et al	2023	a	Students	181	UG	France	MM	?	Support learning, analysis	Recommender, dashboard	X	X		Autonomous learning
Saadati et al	2023	–	Students	33	PG	?	MM	Zimmermann	Support learning	Recommender		X		Collaborative learning
Sáiz-Manzanares et al	2024	a	Students	57	UG, PG	?	MM	Roman & Poggioli	Support learning AI attitude	Chatbot		X		Achievement, Satisfaction
Sandoval Peña et al	2023	a	Students	32	HE	Peru	Quanti	?	Support learning	Chatbot		X		Autonomous learning

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Seidel et al	2021	🔓	Students	180 + 314	HE	?	Quanti	Zimmermann	Support learning	Dashboard		X		Achievement
Song & Kim	2021	–	Students	56	PG	USA	Quanti	?	Support learning	Chatbot	X		X	Achievement, engagement
Sun et al	2023	🔓	Students	182	PG	Taiwan	Quanti	Zimmermann	Support learning	Dashboard	X	X		Achievement
Suraworachet et al	2024	🔓	Students	44	PG	UK	MM	SSRL	Analysis	LLM to predict SRL	X	X	X	Collaborative learning
Taub et al	2021	–	Students	65	UG, PG	North America	Quanti	Winne & Hadwin	Support learning, analysis	Mood detection	X	X		Emotions
Üstün et al	2022	–	Students	62	UG	Turkiye	MM	?	Support learning AI attitude	Dashboard		X		Achievement
Xia et al	2023	🔓	Students	323	HS	China	Quanti	?	Support learning	Chatbot		X	X	Motivation, satisfaction
Wang et al	2024	–	Students	71	UG	Taiwan	Quanti	?	Support learning	Mood detection, automatic feedback	X	X	X	Motivation
Wiedbusch et al	2023	🔓	Students	50	UG	North America	Quanti	Efklides MASRL	Support learning	Eye tracking, ITS		X		Emotions

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Wu et al	2024	–	Students	70	HS	Taiwan	Quanti	Zimmermann	Support learning	ChatGPT		X	X	Motivation, engagement, knowledge construction
Zhang et al	2023	–	Students	15	UG	China	MM	?	Support learning	Chatbot			X	Achievement, motivation

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Profiling and prediction studies (n = 32)

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Afzaal et al	2021		Students & Teachers	157 +	PG	Sweden	MM	?	Support learning Support teaching	Performance prediction	X	X		Achievement, Motivation
Afzaal et al	2023		Students	446 + 356	UG	Sweden	MM	Zimmermann	Support learning	Performance prediction	X	X		Achievement
Borchers et al	2024		Students	10	UG, PG	USA	MM	Winne & Hadwin	Analysis	Profiling SRL	X	X		Achievement
Burman et al	2021		Students	2,011	UG	India	Quanti	?	Support learning	Performance prediction	X	X		Achievement
Chen & Li	2021		Students	17	UG	?	MM	Combination	Analysis	Profiling performance & SRL	X	X		Achievement
Cogliano et al	2022	–	Students	143	UG	?	Quanti	Winne & Hadwin	Support learning	Performance prediction	X			Achievement
Hsu et al	2022		Students	120	HS	Japan	Quanti	?	Analysis	Profiling SRL	X	X		Reading comprehension
Järvelä, Nguyen et al	2023		Students	94	HS	?	Quanti	SSRL	Analysis	Behaviour prediction	X	X	X	Collaborative learning
Lee et al	2021		Students	58	HE	?	Quanti	?	Support learning	Performance prediction		X		Achievement
Li et al	2023		Students	34	UG	North America	Quanti	?	Support learning, analysis	Predict SRL		X		Achievement

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Martens et al	2020		Students	100	HE	Germany	Quanti	?	Analysis	Predict SRL			X	Achievement, emotions, motivation, affective learning
Nuankaew	2020		Students	472	UG	Thailand	Quanti	Zimmermann	Analysis	Profiling SRL	X	X		Satisfaction
Nuankaew	2022		Students	26	HE	Thailand	Quanti	Combination	Analysis	Performance prediction		X		Achievement
Pierrot et al	2023		Students	181	UG	France	MM	?	Support learning, analysis	Profiling SRL	X	X		Autonomous learning
Raković et al	2024		Students	22	UG, PG	Australia	Quanti	Combination	Analysis	Profiling SRL	X	X	X	Engagement
Rientes et al	2019		Students	1,035	UG	Netherlands	Quanti	?	Analysis	Profiling SRL	X	X		Achievement, engagement, emotions
Saadati et al	2023	–	Students	33	PG	?	MM	Zimmermann	Support learning	Predict SRL		X		Collaborative learning
Saint et al	2020	–	Students	239	UG	Australia	Quanti	?	Analysis	Profiling SRL	X	X		Learning behaviour profile

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Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Song et al	2024	–	Students	14,251	HS	USA	Quanti	Zimmermann	Analysis	Profiling SRL	X	X		Achievement, learning behaviour profile
Sun et al	2023		Students	101	PG	Taiwan	Quanti	Zimmermann	Analysis	Profiling SRL		X		Achievement, engagement, cognitive load
Suraworachet et al	2024		Students	44	PG	UK	MM	SSRL	Analysis	LLM to predict SRL	X	X	X	Collaborative learning
Taub et al	2022		Students	250	UG	USA	Quanti	Winne & Hadwin	Analysis	Profiling SRL		X		Achievement
Tu et al	2023	–	Students	303	UG, PG	China	Quanti	?	Analysis	Predicting dropout & SRL	X	X		Student burnout, social support
Vuorenmaa et al	2022	–	Students	92	HS	Finland	Quanti	SSRL	Analysis	Profiling SRL	X	X	X	Engagement, collaborative learning, social interaction
Wang & Lin	2023	–	Students	39	UG	Taiwan	MM	?	Analysis	Profiling SRL	X	X		–
Wiedbusch et al	2022		Students	58	UG	North America	Quanti	Winne & Hadwin	Support learning, analysis	Profiling SRL		X		Achievement

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Xu et al	2023		Students	30	UG	?	Quanti	Zimmermann	Analysis	Profiling SRL	X	X		Collaborative learning, emotions, social interaction
Ye & Pennisi	2022		Students	65	UG, PG	?	MM	Pintrich	Analysis	Performance prediction & profiling SRL	X	X		Learning behaviour profile
Zhang et al	2022	–	Students	4,604	PS, HS	USA	Quanti	Zimmermann	Analysis	Profiling SRL		X		Engagement, social interaction
Zhang, Anders et al	2022		Students	79	MS, HS	USA	Quanti	Winne & Hadwin	Analysis	Profiling SRL	X	X		Problem solving
Zheng et al	2019		Students	144	HS, UG	USA	Quanti	Combination	Analysis	Profiling SRL & SSRL	X	X		Collaborative learning
Zhidkikh et al	2023		Students, Teachers	20 + 2	HS	Finland	MM	?	Analysis	Profiling SRL	X	X		Learning behaviour profile

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Intelligent tutoring system studies (n = 28)

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Borchers et al	2024		Students	10	UG, PG	USA	MM	Winne & Hadwin	Support learning	Stoichiometry Tutor	X	X		Achievement
Bouchet et al	2018		Students	116	UG	USA	Quanti	?	Support learning AI attitude	MetaTutor			X	Emotions
Cerezo et al	2020		Students	119	UG	?	Quanti	?	Support learning	MetaTutor	X	X		Learning disability
Cloude et al	2020		Students	117	UG	North America	Quanti	Winne & Hadwin	Support learning	MetaTutor		X	X	Achievement
da Rocha et al	2024		Students	39	?	Brazil	Quanti	?	Support learning	OLM-based ITS		X		Achievement
Dever et al	2022		Students	105	UG	North America	Quanti	triple SRL–SRT processes	Support learning	MetaTutor	X	X		Achievement

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Dever et al	2023		Students	117	UG	North America	Quanti	?	Support learning	MetaTutor	X	X		Achievement
Harati et al	2021		Students	120	UG	USA	MM	Zimmermann	Support learning AI attitude	ALEKS	X	X	X	–
Huang et al	2023		Students	31	UG	North America	Quanti	?	Support learning	BioWorld	X	X		Reasoning
Huang, Li & Lajoie	2023		Students	32	UG	North America	Quanti	Zimmermann	Support learning	BioWorld	X	X		Engagement, reasoning
Kooken et al	2021		Students	449	MS, HS	USA, Argentina	Quanti	Zimmermann	Support learning	MathSpring	X	X	X	Achievement, emotions
Lajoie et al	2023		Students	30	UG	?	Quanti	Zimmermann	Support learning	BioWorld		X		Reasoning
Li et al	2021		Students	21	UG	North America	Quanti	Zimmermann	Support learning	BioWorld		X		Reasoning, emotions

Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Li et al	2023		Students	34	UG	North America	Quanti	?	Support learning, analysis	BioWorld		X		Achievement
Liu et al	2024	–	Students	48	HS	China	Quanti	?	Support learning	MIATS		X		Achievement
Miller & Bernacki	2019	–	Students	32	UG	–	MM	Situated SRL	Support learning	ALEKS	X	X		Achievement, engagement, motivation
Munshi et al	2023	–	Students	98	MS	USA	Quanti	Combination	Support learning	Betty's Brain	X	X	X	Achievement, emotions
Nagashima et al	2022		Students	26	MS	USA	Quanti	?	Support learning	Choice-based ITS	X			Achievement, problem solving

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Author	Year	OA[a]	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Serrano et al	2018	–	Students	115	HS	Spain	Quanti	?	Support learning	TuinLECweb		X		Reading comprehen-sion
Taub & Azevedo	2019		Students	194	UG	North America	Quanti	Winne & Hadwin	Support learning	MetaTutor	X	X		Achievement
Taub et al	2021	–	Students	65	UG, PG	North America	Quanti	Winne & Hadwin	Support learn-ing, analysis	MetaTutor	X	X		Emotions
Taub et al	2022		Students	250	UG	USA	Quanti	Winne & Hadwin	Support learn-ing, analysis	OLM		X		Achievement
Wei	2023		Students	60	UG	China	MM	?	Support learning AI atti-tude	DuoLingo	X			Achieve-ment, motivation
Wiedbusch et al	2020		Students	55	UG	North America	Quanti	?	Support learning	MetaTutor		X		–
Wiedbusch et al	2021		Students	190	UG	North America	Quanti	Winne & Hadwin	Support learning	MetaTutor	X	X		–
Wiedbusch et al	2022		Students	58	UG	North America	Quanti	Winne & Hadwin	Support learn-ing, analysis	MetaTutor		X		Achievement
Wiedbusch et al	2023		Students	50	UG	North America	Quanti	Efklides MASRL	Support learning	MetaTutor		X		Emotions
Zhang et al	2022		Students	52	MS	USA	Quanti	?	Support learning	CTSiM OELE	X			Achievement

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Assessment and evaluation studies (n = 3)

Author	Year	OA	Participants	# Participants	Study level	Country	Approach	Theoretical framework	Role of AI	AI application	Direct impact			End outcomes
											Cog	Metacog	Motiv	
Ortega-Orchoa et al	2024		Students	196	HE	Spain	Quanti	?	Support learning	Automated grading	X	X	X	Achievement, reasoning, motivation
Sun et al	2023		Students	182	PG	Taiwan	Quanti	Zimmermann	Support learning	Automated grading	X	X		Achievement
Watts et al	2023		Students	5	UG	USA	Quali	Formative-SRL	Support learning	Automated grading	X			–

PS = Primary School, MS = Middle School, HS = High School, HE = Higher Education (level unknown), UG = Undergraduate, PG = Postgraduate, MM = Mixed methods, Quant = Quantitative, Quali = Qualitative, ? = Unclear, Cog. = Cognitive, Metacog. = Metacognition, Motiv. = Motivation, HOTS = Higher order thinking skills

Appendix 2: Geographical distribution of authors

Rank	Country	Count	Percentage
1	United States	36	42.9
2	China	13	15.5
3	Canada	8	9.5
4	Taiwan	7	8.3
5	Spain	6	7.1
6	Finland	5	6.0
=	Germany	5	6.0
=	UK	5	6.0
7	Australia	3	3.6
=	Thailand	3	3.6
8	France	2	2.4
=	India	2	2.4
=	Malaysia	2	2.4
=	Saudi Arabia	2	2.4
=	Sweden	2	2.4
9	Bangladesh	1	1.2
=	Brazil	1	1.2
=	Egypt	1	1.2
=	Estonia	1	1.2
=	Greece	1	1.2
=	Israel	1	1.2
=	Japan	1	1.2
=	Netherlands	1	1.2
=	Pakistan	1	1.2
=	Peru	1	1.2
=	Portugal	1	1.2
=	Russia	1	1.2
=	Singapore	1	1.2
=	South Korea	1	1.2
=	Turkiye	1	1.2

Rank	Continent	Count	Percentage
1	North America	40	47.6
2	Asia	27	32.1
3	Europe	25	29.8
4	Middle East	4	4.8
5	Oceania	3	3.6
6	South America	2	2.4
7	Africa	1	1.2

Appendix 3: Discipline of study participants

Rank	Discipline	Count	Percentage
1	Natural Sciences, Maths & Stats	33	39.3
2	IT / Computer Science	17	20.2
3	Health & Welfare	14	16.7
4	Arts, Hums & Languages	12	14.3
5	Unclear	8	9.5
=	Education	8	9.5
6	Business, Admin & Law	5	6.0
7	Social Sciences, Journalism & Information	4	4.8
8	Engineering, Manufacturing & Construction	2	2.4
9	"STEM"	1	1.2

Study participant discipline by study level

	N	AH&L	Bus & Law	Education	Engineering	H & W	IT	NSM&S	SSJ&I	Unclear	"STEM"
Any higher education	62	13%	8%	13%	3%	21%	26%	29%	6%	11%	2%
Undergraduate	48	17%	10%	10%	4%	25%	21%	35%	2%	13%	2%
Middle / high school	20	15%	0%	0%	0%	5%	0%		0%	5%	5%
Postgraduate	13	15%	15%	31%	8%	23%	31%	23%	23%	8%	0%
Higher education (unknown level)	8	0%	0%	13%	0%	13%	50%	13%	13%	13%	0%
Not explicitly mentioned	2	0%	0%	0%	0%	0%	50%	50%	0%	0%	0%
Primary school	1		0%	0%	0%	0%	0%	0%	0%	0%	0%

AH&S = Arts, Humanities & Languages, Bus & Law = Business & Law, H & W = Health & Welfare, IT = Computer Science, NSM&S = Natural Sciences, Mathematics & Statistics, SSJ&I = Social Sciences, Journalism & Information

Appendix 4: Geographical distribution of study participants

Rank	Country	Count	Percentage
1	Not mentioned	18	21.4
2	USA	15	17.9
3	North America (country not mentioned)	13	15.5
4	China	9	10.7
5	Taiwan	6	7.1
6	Spain	3	3.6
=	Thailand	3	3.6
7	Australia	2	2.4
=	Finland	2	2.4
=	Sweden	2	2.4
9	Argentina	1	1.2
=	Brazil	1	1.2
=	Egypt	1	1.2

Rank	Country	Count	Percentage
=	France	1	1.2
=	Germany	1	1.2
=	India	1	1.2
=	Japan	1	1.2
=	Malaysia	1	1.2
=	Netherlands	1	1.2
=	Peru	1	1.2
=	Turkiye	1	1.2
=	UK	1	1.2

Rank	Continent	Count	Percentage
1	North America	28	33.3
2	Asia	21	25.0
3	Europe	11	13.1
4	South America	3	3.6
5	Oceania	2	2.4
6	Africa	1	1.2
=	Middle East	1	1.2

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Seyyed Kazem Banihashem: Conceptualization, Analysis, Writing original draft, Review. Melissa Bond: Writing, Method, Analysis, Review. Nina Bergdahl: Writing, Review, Edit. Hassan Khosravi: Analysis, Review, Edit. Omid Noroozi**:** Conceptualization, Analysis, Review, Edit.

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Declarations

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References

***indicates that the article is featured in the corpus of the review**

Afzaal, M., Nouri, J., Zia, A., Papapetrou, P., Fors, U., Wu, Y., Li, X., & Weegar, R. (2021). Explainable AI for data-driven feedback and intelligent action recommendations to support students self-regulation. *Frontiers in Artificial Intelligence, 4*, Article 723447. https://doi.org/10.3389/frai.2021.723447*

Afzaal, M., Zia, A., Nouri, J., & Fors, U. (2024). Informative feedback and explainable AI-based recommendations to support students' self-regulation. *Technology, Knowledge and Learning, 29*(1), 331–354. https://doi.org/10.1007/s10758-023-09650-0*

Akinwalere, S. N., & Ivanov, V. (2022). Artificial intelligence in higher education: Challenges and opportunities. *Border Crossing, 12*(1), 1–15.

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., Wortha, F., & Cerezo, R. (2022). Lessons learned and future directions of MetaTutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology, 13*, Article 813632. https://doi.org/10.3389/fpsyg.2022.813632

Baars, M., & Wijnia, L. (2018). The relation between task-specific motivational profiles and training of self-regulated learning skills. *Learning and Individual Differences, 64*, 125–137. https://doi.org/10.1016/j.lindif.2018.05.007
Baars, M., Wijnia, L., & Paas, F. (2017). The association between motivation, affect, and self-regulated learning when solving problems. *Frontiers in Psychology, 8*, 1346. https://doi.org/10.3389/fpsyg.2017.01346
Banihashem, S. K., Kerman, N. T., Noroozi, O., Moon, J., & Drachsler, H. (2024). Feedback sources in essay writing: Peer-generated or AI-generated feedback? *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-024-00455-4
Banihashem, S. K., Noroozi, O., Khosravi, H., Schunn, C. D., & Drachsler, H. (2025). Pedagogical framework for hybrid intelligent feedback. *Innovations in Education and Teaching International*. https://doi.org/10.1080/14703297.2025.2499174
Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. *Educational Research Review, 37*, Article 100489. https://doi.org/10.1016/j.edurev.2022.100489
Berglas-Shapiro, T., Eylon, B. S., & Scherz, Z. (2017). A technology-enhanced intervention for self-regulated learning in science. *Teachers College Record, 119*(13), 1–26. https://doi.org/10.1177/016146811711901301
Bogina, V., Hartman, A., Kuflik, T., & Shulner-Tal, A. (2022). Educating software and AI stakeholders about algorithmic fairness, accountability, transparency and ethics. *International Journal of Artificial Intelligence in Education, 32*, 808–8233. https://doi.org/10.1007/s40593-021-00248-0
Bond, M., Khosravi, H., de Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-023-00436-z
Borchers, C., Zhang, J., Baker, R. S., & Aleven, V. (2024). Using think-aloud data to understand relations between self-regulation cycle characteristics and student performance in intelligent tutoring systems. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 529–539). Association for Computing Machinery. https://doi.org/10.1145/3636555.3636911 *
Bouchet, F., Harley, J. M., & Azevedo, R. (2018). Evaluating adaptive pedagogical agents' prompting strategies effect on students' emotions. In *Intelligent tutoring systems: 14th international conference, ITS 2018, Montreal, QC, Canada, June 11–15, 2018, Proceedings 14* (pp. 33–43). Springer International Publishing. *
Burman, I., Som, S., & Hossain, S. A. (2020). Model for Analyzing Psychological Parameters Recommending Student Learning Behavior. *International Journal of Computing and Digital Systems, 10*, 2–17. https://doi.org/10.12785/ijcds/100188*
Bussey, K., & Bandura, A. (1999). Social cognitive theory of gender development and differentiation. *Psychological Review, 106*(4), 676–713. https://doi.org/10.1037/0033-295x.106.4.676
Butler, D., & Cartier, S. (2018). Advancing research and practice about self-regulated learning: The promise of in-depth case study methodologies. In D. Schunk & J. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 353–369). Routledge.
Cassidy, S. (2011). Self-regulated learning in higher education: Identifying key component processes. *Studies in Higher Education, 36*(8), 989–1000. https://doi.org/10.1080/03075079.2010.503269
Cerezo, R., Esteban, M., Vallejo, G., Sanchez-Santillan, M., & Nuñez, J. (2020). Differential efficacy of an intelligent tutoring system for university students: A case study with learning disabilities. *Sustainability, 12*(21), 9184. https://doi.org/10.3390/su12219184*
Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5–6), 318–331. https://doi.org/10.1504/IJTEL.2012.051815
Chen, K. Z., & Li, S. C. (2021). Sequential, typological, and academic dynamics of self-regulated learners: Learning analytics of an undergraduate chemistry online course. *Computers and Education: Artificial Intelligence, 2*, Article 100024. https://doi.org/10.1016/j.caeai.2021.100024*
Chiu, T. K. (2024). A classification tool to foster self-regulated learning with generative artificial intelligence by applying self-determination theory: A case of ChatGPT. *Educational Technology Research and Development, 72*(4), 2401–2416. https://doi.org/10.1007/s11423-024-10366-w
Cloude, E. B., Wortha, F., Dever, D. A., & Azevedo, R. (2020). How do emotions change during learning with an intelligent tutoring system? Metacognitive monitoring and performance with metatutor. In *CogSci*. *
Cogliano, M., Bernacki, M. L., Hilpert, J. C., & Strong, C. L. (2022). A self-regulated learning analytics prediction-and-intervention design: Detecting and supporting struggling biology students. *Journal of Educational Psychology, 114*(8), 1801. https://doi.org/10.1037/edu0000745*
Cope, B., Kalantzis, M., & Searsmith, D. (2021). Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. *Educational Philosophy and Theory, 53*(12), 1229–1245. https://doi.org/10.1080/00131857.2020.1728732
Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Aldraiweesh, A., Alturki, U., Almutairy, S., Shutaleva, A., & Soomro, R. B. (2024). Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. *Heliyon, 10*(8), Article e29317. https://doi.org/10.1016/j.heliyon.2024.e29317*
Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education, 210*, Article 104967. https://doi.org/10.1016/j.compedu.2023.104967*
Daumiller, M., & Dresel, M. (2019). Supporting self-regulated learning with digital media using motivational regulation and metacognitive prompts. *The Journal of Experimental Education, 87*(1), 161–176. https://doi.org/10.1080/00220973.2018.1448744
Debets, T., Banihashem, S. K., Joosten-Ten Brinke, D., Vos, T. E., de Buy Wenniger, G. M., & Camp, G. (2025). Chatbots in education: A systematic review of objectives, underlying technology and theory, evaluation criteria, and impacts. *Computers & Education*. https://doi.org/10.1016/j.compedu.2025.105323
Dever, D. A., Sonnenfeld, N. A., Wiedbusch, M. D., & Azevedo, R. (2022). Pedagogical agent support and its relationship to learners' self-regulated learning strategy use with an intelligent tutoring system. In *International conference on artificial intelligence in education* (pp. 332–343). Cham: Springer International Publishing

Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way* (Vol. 2156). Springer. https://doi.org/10.1007/978-3-030-30371-6
Doğan, M. E., Goru Doğan, T., & Bozkurt, A. (2023). The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. *Applied Sciences, 13*(5), 3056. https://doi.org/10.3390/app13053056
Domínguez, C., Garcia-Izquierdo, F. J., Jaime, A., Pérez, B., Rubio, A. L., & Zapata, M. A. (2021). Using process mining to analyze time distribution of self-assessment and formative assessment exercises on an online learning tool. *IEEE Transactions on Learning Technologies, 14*(5), 709–722. https://doi.org/10.1109/TLT.2021.3119224*
Doo, M. Y., & Bonk, C. J. (2020). The effects of self-efficacy, self-regulation and social presence on learning engagement in a large university class using flipped Learning. *Journal of Computer Assisted Learning, 36*(6), 997–1010. https://doi.org/10.1111/jcal.12455
Doran, G. T. (1981). There's a SMART way to write managements's goals and objectives. *Management Review, 70*(11), 35–36.
Drzyzga, G., Harder, T., & Janneck, M. (2023). Cognitive effort in interaction with software systems for self-regulatio—An eye-tracking study. In D. Harris & W.-C. Li (Eds.), *Lecture notes in computer science. Engineering psychology and cognitive ergonomics* (Vol. 14017, pp. 37–52)*. Springer. https://doi.org/10.1007/978-3-031-35392-5_3
Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist, 46*(1), 6–25. https://doi.org/10.1080/00461520.2011.538645
Fan, Y., Lim, L., Van der Graaf, J., Kilgour, J., Raković, M., Moore, J., Molenaar, I., Bannert, M., & Gašević, D. (2022). Improving the measurement of self-regulated learning using multi-channel data. *Metacognition and Learning, 17*(3), 1025–1055. https://doi.org/10.1007/s11409-022-09304-z
Ferrara, S., & Qunbar, S. (2022). Validity arguments for AI-based automated scores: Essay scoring as an illustration. *Journal of Educational Measurement, 59*(3), 288–313. https://doi.org/10.1111/jedm.12333
Ferreira da Rocha, F. D., Lemos, B., Henrique de Brito, P., Santos, R., Rodrigues, L., Isotani, S., & Dermeval, D. (2024). Gamification and open learner model: An experimental study on the effects on self-regulatory learning characteristics. *Education and Information Technologies, 29*(3), 3525–3546. https://doi.org/10.1007/s10639-023-11906-2*
Gough, D., Oliver, S., & Thomas, J. (Eds.). (2012). *An introduction to systematic reviews*. SAGE Publication.
Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information and Libraries Journal, 26*(2), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x
Greene, J. A., & Azevedo, R. (2007). A theoretical review of Winne and Hadwin's model of self-regulated learning: New perspectives and directions. *Review of Educational Research, 77*(3), 334–372. https://doi.org/10.3102/003465430303953
Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, Pubmed and 26 other resources. *Research Synthesis Methods, 11*(2), 181–217. https://doi.org/10.1002/jrsm.1378
Hadwin, A. F., Järvelä, S., & Miller, M. (2011). Self-regulated, co-regulated, and socially shared regulation of learning. *Handbook of Self-Regulation of Learning and Performance, 30*, 65–84.
Harati, H., Sujo-Montes, L., Tu, C.-H., Armfield, S., & Yen, C.-J. (2021). Assessment and learning in knowledge spaces (ALEKS) adaptive system impact on students' perception and self-regulated learning skills. *Education Sciences, 11*(10), 603. https://doi.org/10.3390/educsci11100603*
Hartley, K., Hayak, M., & Ko, U. H. (2024). Artificial Intelligence supporting independent student learning: An evaluative case study of ChatGPT and learning to code. *Education Sciences, 14*(2), 120. https://doi.org/10.3390/educsci14020120*
Harzing, A. W. (2007). *Publish or Perish*, available from https://harzing.com/resources/publish-or-perish
Hashem, R., Ali, N., El Zein, F., Fidalgo, P., & Khurma, O. A. (2024). AI to the rescue: Exploring the potential of ChatGPT as a teacher ally for workload relief and burnout prevention. *Research & Practice in Technology Enhanced Learning*. https://doi.org/10.58459/rptel.2024.19023
Heikkinen, S., Saqr, M., Malmberg, J., & Tedre, M. (2023). Supporting self-regulated learning with learning analytics interventions—A systematic literature review. *Education and Information Technologies, 28*(3), 3059–3088. https://doi.org/10.1007/s10639-022-11281-4
Hsu, C. Y., Horikoshi, I., Li, H., Majumdar, R., & Ogata, H. (2022). Extracting students' self-regulation strategies in an online extensive reading environment using the experience API (xAPI). In *30th international conference on computers in education conference, ICCE 2022* (pp. 326–331). Asia-Pacific Society for Computers in Education. *
Huang, A. Y., Lu, O. H., & Yang, S. J. (2023b). Effects of artificial Intelligence-Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers & Education, 194*, Article 104684. https://doi.org/10.1016/j.compedu.2022.104684
Huang, X., Li, S., Wang, T., Pan, Z., & Lajoie, S. P. (2023a). Exploring the co-occurrence of students' learning behaviours and reasoning processes in an intelligent tutoring system: An epistemic network analysis. *Journal of Computer Assisted Learning, 39*(5), 1701–1713. https://doi.org/10.1111/jcal.12827*
Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist, 48*(1), 25–39. https://doi.org/10.1080/00461520.2012.748006
Järvelä, S., Järvenoja, H., Malmberg, J., Isohätälä, J., & Sobocinski, M. (2016). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? *Learning and Instruction, 43*, 39–51. https://doi.org/10.1016/j.learninstruc.2016.01.005
Järvelä, S., Molenaar, I., & Nguyen, A. (2023a). Advancing SRL Research with Artificial Intelligence. *Computers in Human Behavior, 107*, 847. https://doi.org/10.1016/j.chb.2023.107847
Järvelä, S., Nguyen, A., & Hadwin, A. (2023b). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology, 54*, 1057–1076. https://doi.org/10.1111/bjet.13325*
Järvelä, S., Nguyen, A., Vuorenmaa, E., Malmberg, J., & Järvenoja, H. (2023c). Predicting regulatory activities for socially shared regulation to optimize collaborative learning. *Computers in Human Behavior, 144*, Article 107737. https://doi.org/10.1016/j.chb.2023.107737*

Jebur, G., Al-Samarraie, H., & Alzahrani, A. I. (2022). An adaptive Metalearner-based flow: A tool for reducing anxiety and increasing self-regulation. *User Modeling and User-Adapted Interaction, 32*(3), 469–501.*

Kara, M., Kukul, V., & Çakır, R. (2021). Self-regulation in three types of online interaction: How does it predict online pre-service teachers' perceived learning and satisfaction? *The Asia-Pacific Education Researcher, 30*(1), 1–10. https://doi.org/10.1007/s40299-020-00509-x

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Kitto, K., Hicks, B., & Buckingham Shum, S. (2023). Using causal models to bridge the divide between big data and educational theory. *British Journal of Educational Technology, 54*(5), 1095–1124. https://doi.org/10.1111/bjet.13321

Kong, S.-C., & Yang, Y. (2024). A human-centered learning and teaching framework using generative artificial intelligence for self-regulated learning development through domain knowledge learning in K–12 settings. *IEEE Transactions on Learning Technologies, 17*, 1588–1599. https://doi.org/10.1109/TLT.2024.3392830*

Kooken, J. W., Zaini, R., & Arroyo, I. (2021). Simulating the dynamics of self-regulation, emotion, grit, and student performance in cyber-learning environments. *Metacognition and Learning, 16*(2), 367–405. https://doi.org/10.1007/s11409-020-09252-6*

Kramarski, B., & Heaysman, O. (2021). A conceptual framework and a professional development model for supporting teachers' "triple SRL–SRT processes" and promoting students' academic outcomes. *Educational Psychologist, 56*(4), 298–311. https://doi.org/10.1080/00461520.2021.1985502

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33*(1), 159–174. https://doi.org/10.2307/2529310

Lee, H. Y., Chen, P. H., Wang, W. S., Huang, Y. M., & Wu, T. T. (2024). Empowering ChatGPT with guidance mechanism in blended learning: Effect of self-regulated learning, higher-order thinking skills, and knowledge construction. *International Journal of Educational Technology in Higher Education, 21*(1), 16. https://doi.org/10.1186/s41239-024-00447-4*

Lee, S., & Chung, J. Y. (2019). The machine learning-based dropout early warning system for improving the performance of dropout prediction. *Applied Sciences, 9*(15), 3093. https://doi.org/10.3390/app9153093

Lenne, D., Abel, M. H., Trigano, P., & Leblanc, A. (2008). Self-regulated learning in technology enhanced learning environments: An investigation with university students. *Technology, Pedagogy and Education, 17*(3), 171–181. https://doi.org/10.1080/14759390802383751

Li, S., Zheng, J., Huang, X., & Wang, T. (2023). Detection of Goal Setting and Planning in Self-regulated Learning Using Machine Learning and Think-aloud Protocols. In *ISLS conference, Montreal*. https://repository.isls.org/bitstream/1/10375/1/ICLS2023_982-985.pdf *

Liao, X., Zhang, X., Wang, Z., & Luo, H. (2024). Design and implementation of an AI -enabled visual report tool as formative assessment to promote learning achievement and self-regulated learning: An experimental study. *British Journal of Educational Technology, 55*(3), 1253–1276. https://doi.org/10.1111/bjet.13424*

Liu, H., Zhang, Y., & Jia, J. (2024). The design of guiding and adaptive prompts for intelligent tutoring systems and its effect on students' mathematics learning. *IEEE Transactions on Learning Technologies, 17*, 1379–1389. https://doi.org/10.1109/TLT.2024.3382000*

Martens, T., Niemann, M., & Dick, U. (2020). Sensor measures of affective leaning. *Frontiers in Psychology, 11*, 379. https://doi.org/10.3389/fpsyg.2020.00379*

McCarthy, J. (2007). *What is artificial intelligence*. Stanford University. Available at https://www-formal.stanford.edu/jmc/whatisai.pdf

McClelland, M. M., & Cameron, C. E. (2012). Self-regulation in early childhood: Improving conceptual clarity and developing ecologically valid measures. *Child Development Perspectives, 6*(2), 136–142. https://doi.org/10.1111/j.1750-8606.2011.00191.x

Miller, C. J., & Bernacki, M. L. (2019). Training preparatory mathematics students to be high ability self-regulators: Comparative and case-study analyses of impact on learning behavior and achievement. *High Ability Studies, 30*(1–2), 167–197. https://doi.org/10.1080/13598139.2019.1568829*

Molenaar, I. (2022). The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning. *Computers in Human Behavior Reports, 4*, 100130. https://doi.org/10.1016/j.chbr.2022.100130

Molenaar, I., de Mooij, S., Azevedo, R., Bannert, M., Järvelä, S., & Gašević, D. (2023). Measuring self-regulated learning and the role of AI: Five years of research using multimodal multichannel data. *Computers in Human Behavior, 139*, 107540. https://doi.org/10.1016/j.chb.2022.107540

Moon, J., Yeo, S., Banihashem, S. K., & Noroozi, O. (2024). Using multimodal learning analytics as a formative assessment tool: Exploring collaborative dynamics in mathematics teacher education. *Journal of Computer Assisted Learning, 40*(6), 2753–2771. https://doi.org/10.1111/jcal.13028

Mousavinasab, E., Zarifsanaiey, N., Niakan-Kalhori, S. R., Rakhshan, M., Keikha, L., & Ghazi-Saeedi, M. (2021). Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments, 29*(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257

Nagashima, T., Tseng, S., Ling, E., Bartel, A. N., Vest, N. A., Silla, E. M., Alibali, M. W., & Aleven, V. (2022). Students' self-regulated use of diagrams in a choice-based Intelligent Tutoring System. In *Proceedings of the 16th international conference of the learning sciences, ICLS 2022*. https://par.nsf.gov/biblio/10472811 *

Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. *British Journal of Educational Technology, 55*(4), 1328–1353. https://doi.org/10.1111/bjet.13454*

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies, 28*(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218. https://doi.org/10.1080/03075070600572090

Ning, H. K., & Downing, K. (2012). Influence of student learning experience on academic performance: The mediator and moderator effects of self-regulation and motivation. *British Educational Research Journal, 38*(2), 219–237. https://doi.org/10.1080/01411926.2010.538468

Noroozi, O., Alikhani, I., Järvelä, S., Kirschner, P. A., Juuso, I., & Seppänen, T. (2019). Multimodal data to design visual learning analytics for understanding regulation of learning. *Computers in Human Behavior, 100*, 298–304. https://doi.org/10.1016/j.chb.2018.12.019

Noroozi, O., Soleimani, S., Farrokhnia, M., & Banihashem, S. K. (2024). Generative AI in education: Pedagogical, theoretical, and methodological perspectives. *International Journal of Technology in Education, 7*(3), 373–385. https://doi.org/10.46328/ijte.845

Nuankaew, P. (2020). Clustering of mindset towards self-regulated learning of undergraduate students at the University of Phayao. *Advances in Science, Technology and Engineering Systems Journal, 5*(4), 676–685.*

Nuankaew, P. (2022). Self-regulated learning model in educational data mining. *International Journal of Emerging Technologies in Learning (iJET), 17*(17), 4–27. https://doi.org/10.3991/ijet.v17i17.23623

Ortega-Ochoa, E., Quiroga Pérez, J., Arguedas, M., Daradoumis, T., & Marquès Puig, J. M. (2024). The effectiveness of empathic chatbot feedback for developing computer competencies, motivation, self-regulation, and metacognitive reasoning in online higher education. *Internet of Things, 25*, Article 101101. https://doi.org/10.1016/j.iot.2024.101101*

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ (Clinical Research Ed.), 372*, n71. https://doi.org/10.1136/bmj.n71

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*, Article 250270. https://doi.org/10.3389/fpsyg.2017.00422

Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using learning analytics to scale the provision of personalised feedback. *British Journal of Educational Technology, 50*(1), 128–138. https://doi.org/10.1111/bjet.12592

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences*. Blackwell Publishing.

Phillips, D. A., Hutchison, J., Martin, A., Castle, S., Johnson, A. D., Tulsa SEED Study Team. (2022). First do no harm: How teachers support or undermine children's self-regulation. *Early Childhood Research Quarterly, 59*, 172–185. https://doi.org/10.1016/j.ecresq.2021.12.001

Pierrot, L., Michel, C., Broisin, J., Guin, N., Lefevre, M., & Venant, R., (2021). Promoting self-regulated learning strategies for first-year students through the COMPER service. In *18th international conference on cognition and exploratory learning in digital age (CELDA 2021)* (pp. 170–178). *

Pintrich, P. R. (1995). Understanding self-regulated learning. *New Directions for Teaching and Learning, 1995*(63), 3–12. https://doi.org/10.1002/tl.37219956304

Pintrich, P. R. (2000). "The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 452–502). San Diego, CA: Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Raković, M., Li, Y., Foumani, N. M., Salehi, M., Kuhlmann, L., Mackellar, G., Martinez-Maldonado, R., Haffari, G., Swiecki, Z., Li, X., & Gašević, D. (2024). Measuring affective and motivational states as conditions for cognitive and metacognitive processing in self-regulated learning. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 701–712). https://doi.org/10.1145/3636555.3636934 *

Priem, J., Piwowar, H., & Orr, R. (2022). OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. arXiv preprint arXiv:2205.01833. https://doi.org/10.48550/arXiv.2205.01833

Rich, E., & Knight, K. (1991). *Artificial intelligence* (2nd ed.). McGraw-Hill.

Rienties, B., Tempelaar, D., Nguyen, Q., & Littlejohn, A. (2019). Unpacking the intertemporal impact of self-regulation in a blended mathematics environment. *Computers in Human Behavior, 100*, 345–357. https://doi.org/10.1016/j.chb.2019.07.007*

Román, J. M., & Poggioli, L. (2013). *ACRA (r): Escalas de Estrategias de Aprendizaje [Learning Strategies Scales]*. Publicaciones UCAB Doctorate in Education.

Russell, S., & Norvig, P. (2010). *Artificial intelligence: A modern approach* (3rd ed.). Prentice Hall.

Sáiz-Manzanares, M. C., Marticorena-Sánchez, R., Martín-Antón, L. J., González Díez, I., & Almeida, L. (2023). Perceived satisfaction of university students with the use of chatbots as a tool for self-regulated learning. *Heliyon, 9*(1), Article e12843. https://doi.org/10.1016/j.heliyon.2023.e12843*

Sandoval Peña, J., Macalupú Ipanaqué, J., Rufino Sosa, M., García Paz, E., & Morocho Ricalde, C. (2023). Chatbot as an artificial intelligence program in autonomous learning in nursing students at a university in Piura, 2023. *Migration Letters, 20*, 85–104.*

Schraw, G., Kauffman, D. F., & Lehman, S. (2006). Self-regulated learning. *The Encyclopedia of Cognitive Science*. https://doi.org/10.1002/0470018860.s00671

Schunk, D. H., & Zimmerman, B. J. (2013). Self-regulation and learning. In W. M. Reynolds, G. E. Miller, & I. B. Weiner (Eds.), *Handbook of psychology: Educational psychology* (2nd ed., pp. 45–68). London: Wiley. https://doi.org/10.1002/9781118133880.hop207003

Serrano, M. Á., Vidal-Abarca, E., & Ferrer, A. (2018). Teaching self-regulation strategies via an intelligent tutoring system (TuinLECweb): Effects for low-skilled comprehenders. *Journal of Computer Assisted Learning, 34*(5), 515–525. https://doi.org/10.1111/jcal.12256*

Siemens, G., Marmolejo-Ramos, F., Gabriel, F., Medeiros, K., Marrone, R., Joksimovic, S., & de Laat, M. (2022). Human and artificial cognition. *Computers and Education: Artificial Intelligence, 3*, Article 100107. https://doi.org/10.1016/j.caeai.2022.100107

Song, Y., Li, C., Xing, W., Li, S., & Lee, H. H. (2024). A fair clustering approach to self-regulated learning behaviors in a virtual learning environment. In: *Proceedings of the 14th learning analytics and knowledge conference* (pp. 771–778). Association for Computing Machinery. https://doi.org/10.1145/3636555.3636863 *

Stern, C., & Kleijnen, J. (2020). Language bias in systematic reviews: You only get out what you put in. *JBI Evidence Synthesis, 18*(9), 1818–1819. https://doi.org/10.11124/JBIES-20-00361

Su, Y., Lin, Y., & Lai, C. (2023). Collaborating with ChatGPT in argumentative writing classrooms. *Assessing Writing, 57*, Article 100752. https://doi.org/10.1016/j.asw.2023.100752
Sun, J. C. Y., Liu, Y., Lin, X., & Hu, X. (2023). Temporal learning analytics to explore traces of self-regulated learning behaviors and their associations with learning performance, cognitive load, and student engagement in an asynchronous online course. *Frontiers in Psychology, 13*, 1096337. https://doi.org/10.3389/fpsyg.2022.1096337*
Suraworachet, W., Seon, J., & Cukurova, M. (2024). Predicting challenge moments from students' discourse: A comparison of GPT-4 to two traditional natural language processing approaches. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 473–485). https://doi.org/10.1145/3636555.3636905 *
Sutton, A., Clowes, M., Preston, L., & Booth, A. (2019). Meeting the review family: Exploring review types and associated information retrieval requirements. *Health Information and Libraries Journal, 36*(3), 202–222. https://doi.org/10.1111/hir.12276
Swiecki, Z., Khosravi, H., Chen, G., Martinez-Maldonado, R., Lodge, J. M., Milligan, S., Selwyn, N., & Gašević, D. (2022). Assessment in the age of artificial intelligence. *Computers and Education: Artificial Intelligence, 3*, Article 100075. https://doi.org/10.1016/j.caeai.2022.100075
Taub, M., Banzon, A. M., Zhang, T., & Chen, Z. (2022). Tracking changes in students' online self-regulated learning behaviors and achievement goals using trace clustering and process mining. *Frontiers in psychology, 13*, 813514. https://doi.org/10.3389/fpsyg.2022.813514
Thomas, J., Graziosi, S., Brunton, J., Ghouze, Z., O'Driscoll, P., Bond, M., & Koryakina, A. (2022). *EPPI-Reviewer: Advanced Software for Systematic Reviews*. Maps and Evidence Synthesis
Tu, Y., Huang, C., Wu, X., & He, T. (2023). Understanding the determinants of student burnout in blended learning environments. In *2023 3rd international conference on educational technology (ICET)* (pp. 100–104). IEEE. https://doi.org/10.1109/ICET59358.2023.10424157 *
Üstün, A. B., Zhang, K., Karaoğlan-Yilmaz, F. G., & Yilmaz, R. (2023). Learning analytics based feedback and recommendations in flipped classrooms: An experimental study in higher education. *Journal of Research on Technology in Education, 55*(5), 841–857. https://doi.org/10.1080/15391523.2022.2040401*
Vuorenmaa, E., Järvelä, S., Dindar, M., & Järvenoja, H. (2023). Sequential patterns in social interaction states for regulation in collaborative learning. *Small Group Research, 54*(4), 512–550. https://doi.org/10.1177/10464964221137524*
Wang, C. Y., & Lin, J. J. (2023). Utilizing artificial intelligence to support analyzing self-regulated learning: A preliminary mixed-methods evaluation from a human-centered perspective. *Computers in Human Behavior, 144*, Article 107721. https://doi.org/10.1016/j.chb.2023.107721
Wang, W. S., Pedaste, M., Lin, C. J., Lee, H. Y., Huang, Y. M., & Wu, T. T. (2024). Signaling feedback mechanisms to promoting self-regulated learning and motivation in virtual reality transferred to real-world hands-on tasks. *Interactive Learning Environments*, 1–16. *
Watts, F. M., Dood, A. J., & Shultz, G. V. (2023). Automated, content-focused feedback for a writing-to-learn assignment in an undergraduate organic chemistry course. In *LAK23: 13th international learning analytics and knowledge conference* (pp. 531–537). Association for Computing Machinery. https://doi.org/10.1145/3576050.3576053 *
Wei, L. (2023). Artificial intelligence in language instruction: Impact on English learning achievement, L2 motivation, and self-regulated learning. *Frontiers in Psychology, 14*, 1261955. https://doi.org/10.3389/fpsyg.2023.1261955*
Wiedbusch, M., Lester, J., & Azevedo, R. (2023). A multi-level growth modeling approach to measuring learner attention with metacognitive pedagogical agents. *Metacognition and Learning, 18*(2), 465–494.*
Winne, P. H. (1995). Inherent details in self-regulated learning. *Educational Psychologist, 30*(4), 173–187. https://doi.org/10.1207/s15326985ep3004_2
Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Erlbaum.
Wu, T. T., Lee, H. Y., Li, P. H., Huang, C. N., & Huang, Y. M. (2024). Promoting self-regulation progress and knowledge construction in blended learning via ChatGPT-based learning aid. *Journal of Educational Computing Research, 61*(8), 3–31. https://doi.org/10.1177/07356331231191125*
Xia, Q., Chiu, T. K., Chai, C. S., & Xie, K. (2023). The mediating effects of needs satisfaction on the relationships between prior knowledge and self-regulated learning through artificial intelligence chatbot. *British Journal of Educational Technology, 54*(4), 967–986. https://doi.org/10.1111/bjet.13305*
Zawacki-Richter, O., Kerres, M., Bedenlier, S., Bond, M., & Buntins, K. (Eds.). (2020). *Systematic reviews in educational research*. Springer. https://doi.org/10.1007/978-3-658-27602-7
Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(39), 1–27. https://doi.org/10.1186/s41239-019-0171-0
Zimmerman, B. J., & Schunk, D. H. (2011). Self-regulated learning and performance: An introduction and an overview. In *Handbook of self-regulation of learning and performance* (pp. 15–26). Routledge.
Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology, 11*(4), 307–313. https://doi.org/10.1016/0361-476X(86)90027-5
Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2
Zhang, J., Andres, J. M. A. L., Hutt, S., Baker, R. S., Ocumpaugh, J., Nasiar, N., & Young, T. (2022b). Using machine learning to detect SMART model cognitive operations in mathematical problem-solving process. *Journal of Educational Data Mining, 14*(3), 76–108.
Zheng, J., Xing, W., & Zhu, G. (2019). Examining sequential patterns of self-and socially shared regulation of STEM learning in a CSCL environment. *Computers & Education, 136*, 34–48. https://doi.org/10.1016/j.compedu.2019.03.005

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