Received: 8 August 2023 | Accepted: 15 March 2024

DOI: 10.1111/bjet.13459

REVIEW

British Journal of Educational Technology BERA

Self-regulation and shared regulation in collaborative learning in adaptive digital learning environments: A systematic review of empirical studies

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Abstract

Adaptive learning technologies are closely related to learners' self-regulatory processes in individual and collaborative learning. This study presents the outcomes of a systematic literature review of empirical evidence on adaptive learning environments to foster self-regulation and shared regulation of learning in collaborative settings. We provide an overview of what and how adaptive technologies have been used to understand and promote self-regulated learning in collaborative contexts. A search resulted in 59 papers being analysed. Specifically, we identified the seven main objectives (feedback and scaffolding, self-regulatory skills and strategies, learning trajectories, collaborative learning processes, adaptation and regulation, self-assessment, and help-seeking behaviour) that the adaptive technology research has been focusing on. We also summarize the implications derived from the reviewed papers and frame them within seven thematic areas. Finally, this review stresses that future research should consider developing a converging theoretical framework that would enable concrete monitoring and support for self-regulation and socially shared regulation of learning. Our findings set a baseline to support the adoption and proliferation of adaptive learning technology within self-regulated learning research and development.

KEYWORDS
adaptive learning, adaptive learning environments, collaborative learning, self-regulated learning, socially shared regulation, SRL, SSRL

Practitioner notes

What is already known about this topic

- By providing personalized and learner-centric adaptive learning environments (ADLEs), adaptive learning technology can support and foster self-regulated learning (SRL) practices.
- It is possible to create a more student-centred and effective learning environment by combining adaptive learning and collaborative learning.
- Socially shared regulatory activities can involve planning, monitoring, controlling and reflecting on a group's learning processes.

What this paper adds

- Provides a systematic literature review of empirical evidence on ADLEs, SRL and socially shared regulation of learning (SSRL) in collaborative contexts.
- Summarizes the insights on (S)SRL through ADLEs in collaborative learning.
- Identifies challenges and opportunities for ADLEs to support (S)SRL in collaborative learning.

Implications for practice and/or policy

- Learning analytics and educational technology researchers will be able to use the systematic review as a guide for future research.
- Learning analytics and educational technology practitioners will be able to use the systematic review as a summary of the field's current state.

INTRODUCTION

Self-regulated learning (SRL) and adaptive learning environments (ADLEs) are mutually reinforcing concepts in the domain of educational technology. Self-regulated learning refers to the process of individual self-regulation through which learners activate and sustain cognitions, behaviours and affects, which are systematically oriented towards the attainment of learning goals (Winne & Hadwin, 1998). Meanwhile, ADLEs are educational systems that employ technology and data analysis to modify instructional material in real time, aligning with individual learners' abilities, prior knowledge and learning preferences, thereby optimizing the educational experience for each student (Mikić et al., 2022). The synergy between SRL and ALE is evident as personalized, learner-centred ALEs provide a conducive environment for the practice and development of SRL skills, thus facilitating a more effective learning process (Molenaar et al., 2022).

Collaborative learning is an educational approach involving two or more individuals working together to solve a problem, complete a task or understand a concept, which is based on the principle that learning is a social process that is enhanced by sharing and discussing with others

(O'Donnell & Hmelo-Silver, 2013).[1] The importance of collaborative learning lies in its capacity to foster higher-level thinking, increase retention and develop interpersonal skills through the synergy of shared perspectives and collective problem-solving efforts (Dang et al., 2023). With the increasing emphasis on collaborative learning (CL) in education and ongoing advancements in SRL theory, a novel concept called Socially Shared Regulation of Learning (SSRL) has emerged. This concept extends the principles of SRL from an individualized context into a group or collaborative setting. SSRL refers to the process where an interdependence of regulatory activities among learners is acknowledged and leveraged to achieve shared learning goals. These regulatory activities involve planning, monitoring, controlling and reflecting on a group's learning processes. This means that the process of self-regulation is not confined to individual learners but is shared among the group (Hadwin et al., 2018).

Recently, there have been several systematic reviews in the field of ADLEs focusing on various aspects such as personal traits (Normadhi et al., 2019), roles of different stakeholders (Alajlani et al., 2023); personalization in ADLEs (Shemshack & Spector, 2020), from the point of view of computing education (Jamal et al., 2020), use of artificial intelligence (AI, Kabudi et al., 2021), flipped classrooms (Ainulluluah et al., 2022), and virtual assistants (Gubareva & Lopes, 2020), enhancing student performance (Anindyaputri et al., 2020), prediction of learning paths (Alzahrani et al., 2020) and anatomy of student models (Nakic et al., 2015) to name a few. Similarly, there have been numerous systematic reviews focusing on various aspects of SRL, such as SRL strategies within e-learning (Garcia et al., 2018), distance learning (Edisherashvili et al., 2022) and massive open online courses (MOOCs, Lee et al., 2019), SRL in higher education (Roth et al., 2016) and high schools (Kesuma et al., 2020), open learner models in SRL (Hooshyar et al., 2020), SRL in flipped classrooms (Rasheed et al., 2020), and the impact of learning analytic intervention (Heikkinen et al., 2023), to name a few. There have been relatively few systematic reviews that focus on SSRL in collaborative learning (Sulla et al., 2023), despite their significance for understanding the interplay between individual and collective learning processes. To the best of our knowledge, there are no systematic reviews extracting the knowledge on SRL and SSRL in collaborative learning with ADLEs.

The investigation of SRL and SSRL in collaborative learning facilitated within ADLEs is a complex phenomenon that presents a multifaceted research area and necessitates a nuanced understanding. The interplay between these two forms of regulation in the adaptive context of digital learning environments is not yet fully understood. A systematic review in this area would illuminate how these regulatory processes interact and influence learning outcomes in ADLEs. The interaction between SRL and SSRL in collaborative learning involving ADLEs is complex and not yet fully understood (Järvelä, Molenaar, et al., 2023). While SRL and SSRL have been extensively studied in traditional learning environments, their dynamics within ADLEs require further investigation. A systematic review in this domain would be instrumental in synthesizing existing research and identifying gaps in the literature. To this end, we conducted a systematic review to draw out the state-of-the-art with respect to the following two overarching research questions.

1. How are self-regulation and shared regulation contextualized and measured in collaborative learning in ADLEs?
2. What factors of self-regulation and shared regulation are studied the most in collaborative learning in ADLEs?

To answer these research questions, our study is structured around several pivotal areas to investigate SRL and SSRL in collaborative learning within ADLEs. The first area involves assessing various educational contexts where these phenomena have been studied. These contexts are characterized by elements such as research design, educational domain, learning environment, learning scenario and educational level. This characterization allows for the extraction of specific knowledge pertinent to each context. Additionally, we consider the sample size within these contexts as an indicator of the studies' statistical robustness. The second area of our study focuses on the methodologies of data collection and analysis used in the selected studies. This includes examining the types of data gathered, the analytical methods applied and the social units of analysis. Understanding these elements is essential for comprehending how learners are monitored within these contexts. A crucial component of our research is the exploration of the interconnection between the educational contexts and the measurement methods. To this end, we employ a chi-square analysis of the cross-tabulated codes, which will be detailed in the results section. This analysis is vital for understanding the dynamics between educational settings and measurement strategies. Furthermore, we investigate the research objectives and outcomes of these studies. Through thematic analysis, we aim to uncover key insights, challenges and opportunities within the field. This process involves collaborative theme identification and coding of the objectives and outcomes, offering an empirical perspective on the field's opportunities and challenges.

Finally, our study focuses on identifying the SRL and SSRL factors highlighted in the research. This examination provides a theoretical perspective, enabling us to pinpoint theoretical opportunities and challenges. This comprehensive approach ensures a detailed understanding of the practical and theoretical aspects of self-regulation and shared regulation in ADLEs.

THEORETICAL BACKGROUND

Self-regulated learning (SRL) and adaptive learning environments (ADLEs)

Self-regulated learning (SRL) and ADLEs represent a confluence of learner-centred paradigms reshaping educational practices. Molenaar et al. (2022) have articulated that by offering personalized experiences, ADLEs serve to underpin and augment the practice of SRL. The synergy between SRL and ADLEs is posited to enhance learning efficiency and efficacy, a notion supported by the work of McCaslin and Daniel (2013).

Adaptive learning technologies are characterized by their capacity to deliver content and activities dynamically tailored to the learner's proficiency and developmental trajectory (Mikić et al., 2022; Verpoorten et al., 2009). This adaptive tailoring corresponds closely with SRL principles, particularly the aspects concerning goal setting and targeted focus on areas in need of development, aligning with the research findings of Persico and Steffens (2017) and Nan Cenka et al. (2022).

Furthermore, ADLEs are adept at providing prompt feedback on performance, a feature that is crucial for SRL as it facilitates learners in evaluating their comprehension, recognizing their strengths and learning gaps, and modifying their learning strategies (Bimba et al., 2017; Martin et al., 2020). The seminal work of Butler and Winne (1995) and more recent studies by Chou and Zou (2020) emphasize the importance of feedback for self-regulated learners in their ongoing cognitive assessment and adjustment process.

The centrality of learner autonomy and control within SRL is expounded upon by Lewis and Vialleton (2011) and Murray (2014), highlighting the importance of choice and self-direction in the learning process. This is exemplified in ADLEs, where learners have the discretion to select learning paths, topics and activities that resonate with their interests and learning preferences (Cho et al., 2023). Such environments not only facilitate choice but also encourage learners to engage in reflection and to employ strategies that foster metacognitive skill development, which Lehmann et al. (2014) assert as critical in promoting metacognition.

Moreover, ADLEs are designed to calibrate the complexity and difficulty of content to match learners' existing knowledge base and skill level, thereby supporting the continuous adaptation that is integral to SRL (Code & Zaparyniuk, 2006; Guo, 2022). It is imperative for the efficacy of both SRL and ADLEs that the content presented is engaging and germane to the learner's interests and needs, ensuring the sustenance of the learner's engagement and motivation.

The integration of SRL principles with ADLEs represents a significant advance in educational technology. The personalized, responsive nature of ADLEs harmonizes with the self-directed, goal-oriented essence of SRL, facilitating a more intuitive, responsive and ultimately effective learning experience. This integration highlights the potential for continued innovation in the design of learning systems that cater to the evolving needs of learners, empowering them to take charge of their educational journeys in increasingly sophisticated ways.

From individual to collaborative learning within ADLEs

The contemporary educational landscape suggests a shift towards a more student-centred approach through the incorporation of adaptive and collaborative learning methodologies. Magnisalis et al. (2011) provide evidence that such a combination can cultivate a learning environment that is both effective and centred around the student's individual learning journey. Wu et al. (2005) further posit that the intersection of personalization through adaptive learning with the social dimensions of collaborative learning can significantly enhance interpersonal skill development among learners. Moreover, Verdu et al. (2008) explore the potential of ADLEs to identify and harness students' strengths and weaknesses, thereby facilitating the formation of collaborative groups with balanced, complementary skill sets. This strategic group formation enhances the efficiency and efficacy of collaborative efforts, thereby bolstering collective learning outcomes.

Within the domain of collaborative learning, ADLEs can be programmed to modulate the difficulty level of tasks and discussions, ensuring that learning activities remain challenging and engaging for all participants (Lin, 2020; Paramythis & Mühlbacher, 2008; Srba & Bielikova, 2014). This dynamic adjustment is critical in maintaining an optimal zone of proximal development across diverse learner groups. The blended learning framework, as outlined by Mosa and Kakehi (2012) and de la Fuente-Valentín et al. (2010), integrates adaptive learning with collaborative activities, thereby providing a holistic learning experience. This approach leverages the individualized instruction capabilities of adaptive technologies while simultaneously fostering key collaborative competencies such as teamwork, communication and the appreciation of diverse perspectives (Järvelä et al., 2015 & 2018; Järvelä & Hadwin, 2013).

Moreover, the convergence of individualized adaptive learning pathways with collaborative learning strategies allows for detailed tracking of students' performance and engagement levels. Furugori et al. (2002) and Apoki et al. (2022) suggest that the data gleaned from these interactions can be utilized to deliver personalized feedback, which in turn, can be instrumental in refining group dynamics and enhancing the overall collaborative learning experience.

The integration of ADLEs with collaborative learning practices represents a promising frontier in education. This paradigm aligns with the need for instructional models that support both the unique learning trajectory of the individual and the collective intellectual growth fostered by group interaction. The confluence of these approaches serves to create a rich, responsive and multifaceted educational environment where learning is both an individual and a shared journey, characterized by a continuous cycle of personalization, interaction and adaptation.

Socially shared regulation of learning (SSRL) in ADLEs

In collaborative learning, socially shared regulation of learning (SSRL) refers to the regulatory processes that occur at the group level, where individuals collectively plan, monitor and assess their learning as a cohesive unit. SSRL considers the social, collaborative nature of such learning and highlights the importance of shared cognitive and metacognitive strategies, motivational beliefs and emotional regulation in groups. While SRL is integral to individual academic achievement, SSRL is pivotal to successful collaborative learning. Research has indicated that effective SSRL can lead to higher group performance, better quality of collaboration and enhanced individual learning outcomes in collaborative settings (Järvelä et al., 2016). It also fosters a mutual understanding among group members, which can contribute to developing a shared vision for tasks and strategies, leading to improved group success (Panadero & Järvelä, 2015).

In the context of ADLEs, SSRL operates in conjunction with adaptive technologies to support these group-level regulatory processes. ADLE can enhance SSRL by providing real-time, data-driven insights into group interactions, allowing for the alignment of group activities with collective goals and the optimization of collaborative tasks (Cho & Jonassen, 2009). Moreover, adaptive feedback mechanisms within these environments can serve to scaffold the group's regulatory actions, reinforcing effective collaboration patterns and prompting reflection on group strategies (Järvelä et al., 2015 & 2018).

The incorporation of SSRL in ADLE necessitates sophisticated design features that allow for the capture and analysis of group interactions and progress, thereby enabling the system to adapt to the group's dynamic learning needs (Hadwin et al., 2018). This includes the provision of tools that support group planning, task delegation, progress monitoring and the orchestration of collective reflection sessions, which are essential components of SSRL (Dang et al., 2023).

The convergence of SSRL and ADLE also holds the potential to personalize the learning experience not just at the individual level but also at the group level. Through the use of analytics and adaptive algorithms, these environments can detect when a group may benefit from additional resources, alternative collaborative strategies or changes in group composition, thereby facilitating a more productive and cohesive learning experience (Azevedo et al., 2019).

Nevertheless, in practice, SRL and SSRL are dynamically interwoven; individual members' self-regulatory actions can influence and be influenced by the group's regulatory processes. Effective SSRL is often predicated on the SRL competencies of individual members, as individuals bring their self-regulatory strategies into the group context, where they are negotiated, synchronized and potentially transformed through social interaction. Conversely, experiences within SSRL contexts can enhance individuals' SRL skills by exposing them to diverse regulatory strategies and perspectives. Thus, both forms of regulation are essential for comprehensive learning experiences, particularly in collaborative environments where learning is a shared endeavour.

Despite the recognized importance of examining SRL and SSRL in collaborative learning with ADLEs, the literature reveals that the dynamics of these regulatory processes in adaptive and collaborative digital settings are not fully understood. A systematic review in this domain is essential for several reasons. Firstly, it would synthesize the existing empirical findings on how SRL and SSRL manifest and interact within ADLEs in the context of collaborative learning. Secondly, it would identify the methodological approaches used to study these phenomena, highlighting the strengths and limitations of current research designs. The work of Azevedo et al. (2019) on the adaptive nature of SRL in digital environments lays a foundational understanding of individual regulation in learning. Extending this to collaborative settings, the research by Järvelä et al. (2015) on SSRL provides insights into the collective regulation processes in learning groups. However, the integration of these perspectives within the specific context of ADLEs, where adaptive technologies and collaborative learning intersect, remains underexplored. Such a review would pinpoint gaps in the current understanding, offering directions for future research.

While the literature features numerous systematic reviews on ADLEs (eg, Alajlani et al., 2023; Shemshack & Spector, 2020) and SRL (eg, Heikkinen et al., 2023; Kesuma et al., 2020), reviews focusing on both SRL and SSRL in collaborative contexts are less common. Importantly, there is a distinct gap in systematic reviews examining the intersection of SRL and SSRL within ADLEs. A systematic review of SRL and SSRL in collaborative learning within ADLEs is essential to consolidate current research, highlight educational implications and guide future innovation. As ADLEs evolve, understanding how they support or impede SRL and SSRL is crucial for effective educational design and to inform the integration of technology in learning practices. This review would help clarify how adaptive technologies can better facilitate both individual and group learning processes, ensuring that these environments meet the diverse regulatory needs of learners.

METHODOLOGY

To minimize potential biases (researchers) and support reproducibility (especially in the areas of software engineering and information systems, as well as educational technology) in this systematic review, we follow a transparent and widely accepted process. In addition to minimizing bias and supporting reproducibility, systematic reviews provide information about the impact of a phenomenon across a wide range of settings, contexts and empirical approaches. As a result, systematic reviews can provide evidence that the phenomenon is robust and transferable if the selected studies give consistent results (Kitchenham & Charters, 2007).

Papers collection

Several procedures were followed to ensure a high-quality literature review on ADLEs and SSRL/SRL. A comprehensive search of peer-reviewed papers was conducted in March 2023 (short papers, posters, dissertations, editorials and reports were excluded). To capture the SRL aspects used in the papers we used *'regulated learning' OR 'self-regulated learning' OR SRL OR 'shared regulation' OR 'shared regulated learning'*. To capture the collaborative context we used *'collaborative learning' OR CSCL*. Finally, to capture the adaptive nature of the technology, we used *'adaptive learning' OR 'adaptive learning environments' OR 'personalized learning' OR 'personalized learning' OR 'tailored learning'*. The following search phrase was used.

('regulated learning' OR 'self-regulated learning' OR SRL OR 'shared regulation' OR 'shared regulated learning') AND ('collaborative learning' OR CSCL) AND ('adaptive learning' OR 'adaptive learning environments' OR 'personalized learning' OR 'personalized learning' OR 'tailored learning')

Publications were selected from 2000 onwards because there have been tremendous technological advances since 2000 in data-driven learning analytics and educational data mining. The following databases were searched: SpringerLink, Wiley, Association for Computing Machinery [ACM] Digital Library, IEEE Xplore, Science Direct, SAGE and

ERIC. This selection was inspired by the recent SLRs (Mangaroska & Giannakos, 2018; Papavlasopoulou et al., 2017; Sharma & Giannakos, 2020, 2021). The search process uncovered 812 peer-reviewed papers.

Inclusion and exclusion criteria

The selection phase determines the literature review's overall validity, and thus, it is essential to define specific inclusion and exclusion criteria. We applied eight quality criteria informed by related works (eg, Dybå & Dingsøyr, 2008). In general, the studies had to meet the following three criteria; they had to be (1) rigorous; (2) credible; and (3) relevant. 'Rigorous' refers to the appropriate research method applied to the study, 'credible' points to the presentation and validity of the findings and 'relevant' indicates whether the findings of each study were suitable for education science, as well as computer science education research communities. Specifically, we adopted eight criteria to evaluate the quality of the studies. The scope of this evaluation was to ensure that only high-level studies would contribute to our literature review. The selection phase determines the overall validity of the literature review, and thus, it is important to define specific inclusion and exclusion criteria. Table 1 defines the three-layered sets of selection criteria we applied.

As Dybå and Dingsøyr (2008) specified, the quality criteria need to cover three main issues (ie, rigour, credibility and relevance) that need to be considered when evaluating the quality of the selected studies. We applied eight quality criteria informed by related works (eg, Dybå & Dingsøyr, 2008). We explain this quality criteria using two examples from the papers in this SLR (Hadwin et al., 2018; Harley et al., 2017).

Does the study clearly address the research problem?

The selected papers have clearly explained the problem that the contribution is addressing. For instance, Hadwin et al. (2018) highlight that students often recognize planning problems during collaboration but struggle to identify effective strategies to overcome these challenges.

TABLE 1 Filtering criteria.

Quality criteria	First filter criteria	Second filter criteria
1. Does the study clearly address the research problem? 2. Is there a clear statement of the aims of the research? 3. Is there an adequate description of the context in which the research was carried out? 4. Was the research design appropriate to address the aims of the research? 5. Does the study clearly determine the research methods (subjects, instruments, data collection, data analysis)? 6. Was the data analysis sufficiently rigorous? 7. Is there a clear statement of findings? 8. Is the study of value for research or practice?	1. Papers should be in English only 2. Papers should be published in peer-review venues only (ie, book chapters, opinion papers, editorials and magazine papers were removed) 3. Papers should not be workshop papers, doctoral consortium papers, extended abstracts and keynote texts. Therefore, we removed such contributions. This is also seen in some other recent SLRs published in the related venues (Baykal et al., 2020; Subramanian et al., 2020) 4. Papers should not be duplicated	1. Papers should present empirical data 2. Review papers should be removed 3. If the paper does not include SRL or adaptiveness in the technology presented, it should be removed 4. If the paper presents a learning system that has no aspect of potential collaboration, it should also be removed

In particular, Hadwin et al. (2018) stated that '*Despite reporting planning problems as a main challenge during collaboration, students often fail to identify productive strategies for ameliorating those challenges. In other words, when students recognize planning problems, they don't know what to do about them*'. Similarly, Harley et al. (2017) note that while research on pedagogical agents (PAs) has largely concentrated on their role in externally regulating self-regulated learning (SRL), there has been insufficient attention to how they might facilitate collaborative regulatory processes, such as co-regulated and socially shared regulated learning.

Regarding the clarity of the research aims, the selected papers articulate the primary goals of their contributions effectively. Hadwin et al. (2018) investigate a support tool aimed at enhancing group members' awareness of planning beliefs and processes through the provision of visualizations of these beliefs and perceptions. On the other hand, Harley et al. (2017) tackle existing challenges by developing a theoretically grounded qualitative coding scheme to categorize different learner–PA interaction patterns and exploring the potential relationships between these patterns, including prompt and feedback compliance, and their impact on learning outcomes.

Is there an adequate description of the context in which the research was carried out?

The educational context and learning settings should be described in the papers. The paper by Hadwin et al. (2018) clearly indicated that they are working within collaborative settings (Hadwin et al., 2018), while Harley et al. (2017) explicitly described the human–agent collaboration setting (Harley et al., 2017). Both papers then proceeded to present the sample size, educational levels and the educational domains in the studies.

Was the research design to address the aims of the research?

The research design should match the demands of the research questions. For example, Hadwin et al. (2018) used a sequence of planning and collaborative/individual tasks to examine the awareness of planning beliefs and processes. On the other hand, Harley et al. (2017) used five agents ('*The PAs included Gavin the Guide, Pam the Planner, Mary the Monitor, and Sam the Strategizer*') to support the SRL/SSRL activities.

Does the study clearly determine the research methods (subjects, instruments, data collection, data analysis)?

The research methods should be clearly explained in the paper. In both the examples, subjects (description of student population), data collection (qualitative coding and survey in Hadwin et al., 2018 and log data with think-aloud audio in Harley et al., 2017) and data analysis (mixed-methods in Hadwin et al., 2018 and quantitative analysis in Harley et al., 2017) were clearly provided.

Was the data analysis sufficiently rigorous?

In both examples, the data analysis was sufficiently presented to make sure the research questions were addressed. Hadwin et al. (2018) present the main data analysis as the 'Comparison of visualization conditions on severity of challenges' and 'Comparison of visualization conditions on strategy used to address main challenge' whereas, Harley et al. (2017) have used research questions while explaining the measures as well as results.

Is there a clear statement of findings?

The contributions both present their findings in a concise and clear manner, with each offering clear statements that summarize key outcomes. For instance, Harley et al. (2017) explain that the notable differences observed between the RA and SPF1 profiles under the control condition could be attributed to the learners in the RA profile possessing less initial knowledge specific to subgoal 1 compared to those in the SPF1 profile. Specifically, Harley et al. (2017) wrote that '*The significant finding between RA and SPF1 profiles in the Control condition may be explained by learners in the RA profile having lower initial subgoal 1-specific prior knowledge than those in the SPF1 profile*'. Similarly, Hadwin et al. (2018) found that students who did not receive planning support through visualizations perceived planning as a more significant issue. Hadwin et al. (2018) noted that '*students who received no planning support through visualizations reported planning as a more severe problem*'.

Is the study of value for research or practice?

The contributions included in the SLR should have clear research and/or practice-oriented implications. Both the contributions have explicit implications for research. For example, Hadwin et al. (2018) wrote '*Together these findings lend support for future interventions introducing planning and checking strategies to groups in response to a range of challenges that arise during collaboration*'. Whereas Harley et al. (2017) stated that '*Future research should use the coding scheme developed in this study to collect data from a larger number of learners assigned only to the PF condition where the Co profile was identified*'.

All the coders are experienced researchers in educational technology. All the authors discussed and agreed upon the quality criteria and divided the set of papers into three parts. The papers that were creating any confusion were discussed and agreed upon whether to include them or exclude them. The quality check removed 88 papers. This step was followed by two filters to include/exclude the papers from this review. After applying the first, there were 473 papers left, which were subjected to the second filter. The second filter was based on reading the title and the abstracts of the papers and had the following rules in the second column of Table 1. After applying the second filter, there were 74 papers left. These papers were then subjected to data analysis. While analysing the papers, we observed a further 14 papers that did not fulfil the inclusion criteria. Therefore, the results presented in this systematic literature review are from the remaining 59 papers (Figure 1).

Data analysis

In total, 59 studies (see Appendix B in Supporting Information) were found to meet the quality criteria, as we have stated above. These studies have been coded according to specific areas of focus in which they have been conducted. It was through this process that we were able to consolidate the essence of the studies as well as the main focus of them. It was decided that the categories selected should represent the ADLEs, SRL/SSRL and CL aspects of the paper as well as its objectives and content. We adopted the coding scheme from recent systematic literature reviews (Mangaroska & Giannakos, 2018; Papavlasopoulou et al., 2017; Sharma & Giannakos, 2020, 2021).

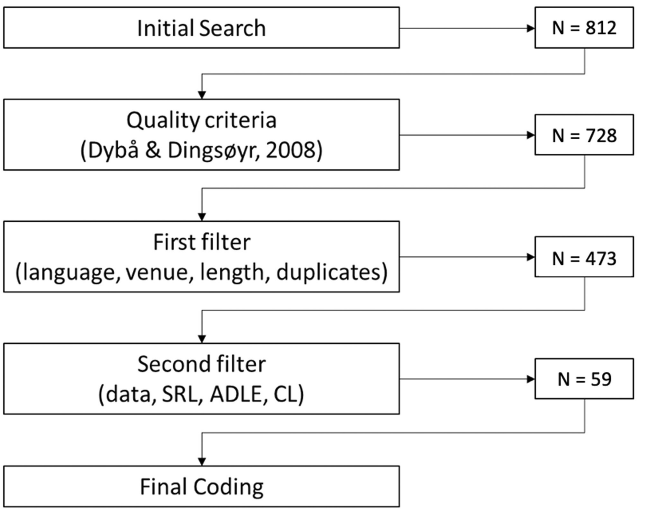

FIGURE 1 Stages of paper collection and filtering.

The educational context provides information about the design of the educational activities. Before designing any educational resource or activity, one has to consider the subcategories presented in Table 2. Research Design, Educational Domain, Learning Environment, Learning Scenario, Educational level and Sample Size provide the basic building blocks of any educational research setup, educational resource or activity. Therefore, in this SLR, we considered it is important to highlight the selected contributions. To extract relevant information about the educational context of the studies, we divided the contextual information into six subcategories. These subcategories and further codes were inspired by relevant SLR in the educational technology and human–computer interaction domains. The Research Design subcategory was named 'category' by Mangaroska and Giannakos (2018) and Sharma and Giannakos (2020). In these two SLRs 'research design' had four codes: experiment, case study, secondary data analysis and ethnography.

Moreover, Sharma and Giannakos (2021) coded the same subcategory as the research design and had the same codes. We extended this subcategory to include design-based research, quasi-experiments, cross-sectional studies, action research, field experiments and longitudinal studies. This was done to provide a richer coding scheme than the previous contributions. The Educational Domain subcategory was also coded as 'research topic' by Mangaroska and Giannakos (2018) and by Sharma and Giannakos (2020) highlighting the educational domains such as STEM, CS, Social sciences, Arts and humanities. Similar codes were present in Papavlasopoulou et al. (2017) as 'subject areas'. We extended the subcategory with education, psychology, healthcare and medicine, business and management, communication sciences, literature and economics. This extension provided a richer presentation of the contributions. Next subcategories, learning environment, learning scenario, educational levels and sample size, were directly taken from Papavlasopoulou et al. (2017), Mangaroska and Giannakos (2018) and Sharma and Giannakos (2020, 2021).

The next category, Data Collection and Analysis, provides information about the research equipment used by the selected contributions. We subcategorized them into units of analysis, data collection and analysis methods. Regarding the units of analysis, Mangaroska and Giannakos (2018) coded this into individual, team and class; while Sharma and Giannakos (2020) coded them into the individual and groups/teams. In this paper, we categorized units of analysis into individual, teams and multi-level. We decided not to include class-level units of analysis due to the nature of SRL and SSRL studies that focus on

TABLE 2 Coding scheme for the systematic literature review.

Main category	Subcategory	Codes	Research question
Educational and research context	Research design	Experiment, case study, design-based research, cross-sectional study, quasi-experiment, exploratory study, action research, field experiment, longitudinal studies	RQ1 (context)
	Educational domain	Social sciences, science technology engineering and mathematics (STEM), education, psychology, healthcare and medicine, language, business and management, communication science, literature, economics and others	
	Learning environment	Learning management systems (LMS), online learning (if the course was conducted completely online), blended learning, computer-supported collaborative learning (CSCL), face-to-face learning, ubiquitous learning, virtual reality systems, self-made software (this includes software developed by the research group that does not fall into any of the other categories)	
	Learning scenario	Formal, informal, non-formal	
	Educational level	Graduates, high school, master's, primary, professionals, secondary, teachers, undergraduate university	
	Sample size	<50, >1000, 100–200, 200–300, 300–500, 50–100, 500–1000	
Data collection and analysis	Unit of analysis	Individual, team, or both (multi-level)	RQ1 (measurement)
	Data collection	Audio, discourse, eye-tracking, forum text, interviews, logs, observations, social network analysis, surveys, tests, think-aloud data, video and written text (The number of different data sources used in the studies is also presented)	
	Analysis method	Qualitative, quantitative, mixed-methods, exploratory analysis	
Research objectives and outcomes	Research objective Behaviour performance The impact of adaptive support on (S)SRL and learning outcomes or how to inform adaptive support for (S)SRL	A secondary coding scheme was employed to thematically analyse the research objectives and outcomes. Two authors initially coded 20% of the papers collaboratively to align on themes. Subsequently, another 20% of the papers were coded independently to validate the themes, rectifying any discrepancies. Finally, the remainder of the papers were coded by one author	RQ2

TABLE 2 (Continued)

Main category	Subcategory	Codes	Research question
SRL and SSRL aspects	Regulatory modes	SRL, CoRL, SSRL, unclear	RQ2
	SRL aspects covered	Affective, motivational, cognitive, metacognitive, behavioural, unclear	
	Models of (S)SRL	Boekaerts et al. (2000), Efklides (2006), Hadwin et al. (2011), Pintrich (2004), Winne and Hadwin (1998), Zimmerman (1986) and others	
	SSRL aspects covered	Affective, motivation, cognitive, meta-cognitive, behavioural, unclear	
	Which SRL activities/skills were observed?	Affective, behavioural, cognitive, motivation, planning, reflection, self-monitoring	
		Metacognitive awareness, metacognitive monitoring	
	How are SRL activities/skills observed?	Artefacts, dialogue, discourse, interviews, logs, observations, self-reported, surveys, tests, think-aloud data, video	
	Which SSRL activities/skills were observed?	Same as the SRL skills and the following additional ones: Goal-setting, organization, sustained collaboration, task understanding	
	How are SSRL activities/skills observed?	Artefacts, discourse, interviews, logs, self-reported	
	How was the regulation shared?	Artefacts, discourse, interviews, logs, self-reported	

individual and team-level regulations. The data collection codes the data used in the studies, which gives us an indication of the level of data capture in the studies (similar to Mangaroska & Giannakos, 2018; Papavlasopoulou et al., 2017; Sharma & Giannakos, 2020, 2021). This subcategory provides insight into what aspects of SRL/SSRL can be captured using which data type. For the methodology subcategory, we kept the qualitative, quantitative and mixed-methods codes as presented in the related systematic reviews.

Considering the Research Objectives and Outcomes, we used a bottom-up coding scheme (Figure 2) to subcategorize the research objectives, behaviour performances and the SRL/SSRL aspects of the studies. Such coding schemes were followed in qualitative studies (Lee-Cultura et al., 2022) and other systematic reviews (Sharma & Giannakos, 2020, 2021). Two authors first coded 25% (15 papers) of the papers to establish a previously agreed coding scheme. After reassessing the coding scheme once again after coding 25% of the papers, we coded another 5% (3 papers) of the papers to better understand the changed coding scheme. Finally, the remaining 70% (41 papers) were divided into the two authors and coded separately. The intercoder reliability was 0.72. The figures show the flow of the coding process. This coding scheme was introduced to present and analyse the research objectives and outcomes in a manner that provides further challenges and opportunities in the concerned research areas. The main reason for using a bottom-up coding scheme was the absence of apparent categories in the related systematic reviews or otherwise.

Finally, to capture the SRL and SSRL aspects covered in the selected contributions, the SRL and SSRL-related codes were adopted by combining the models from Efklides (2006), Järvelä

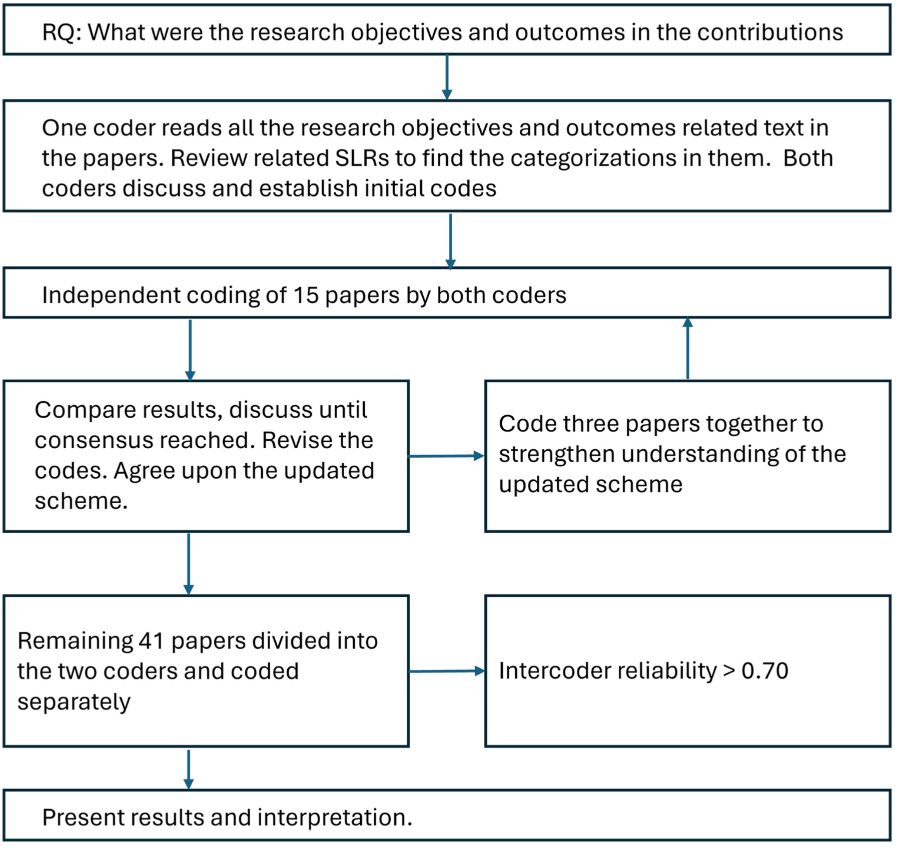

FIGURE 2 The coding scheme for research objectives and outcomes.

and Hadwin (2013) and Pintrich (2000). These three models combine behavioural, cognitive and affective processes (Pintrich, 2000) with metacognitive processes (Efklides, 2006) and are contextualized within collaborative settings (Järvelä & Hadwin, 2013). By categorizing the papers in our literature review, we were able to record all the necessary information from the papers in our literature review and use it to address the research questions we had in mind. In particular, the collected studies were analysed according to the elements presented in Table 2.

The first two code categories answer the first research question, while the last two answer the second. Specifically, to answer the RQ1c, we conducted chi-squared tests on the cross-tabulation of the subcategories one and two. The important thing to note is that papers were coded based on the reported information, that different authors reported information at different levels of granularity, and that in some cases, the information was also missing from the paper. Overall, the authors tried to code the paper as accurately and completely as they could.

RESULTS

Context of the studies (RQ1a)

This section presents state-of-the-art findings from the research context and design perspectives. The codes are provided in Table 2. This includes the research design, educational domain, learning environment, learning scenario, educational level of the participants and the study's sample size. We observe that there were 24 instances of contributions where the researchers used case studies, while 16 studies used a quasi-experimental design; nine contributions presented experiments; five contributions used exploratory studies; five contributions used design-based research; and there were four contributions uniquely using action research, field experiment, longitudinal study and cross-sectional study (Figure 3, left). Concerning the educational domain (Figure 3, right), the majority of papers were situated within the STEM domain (32); 11 papers were situated within social sciences; seven each within education and psychology; two sets of six papers each were situated within healthcare-and-medicine and language-learning; five papers were situated within business and management studies; and one paper was focusing on the students from the following domains: building and construction, literature, economics, and communication sciences. Five other studies did not explicitly mention the educational domain.

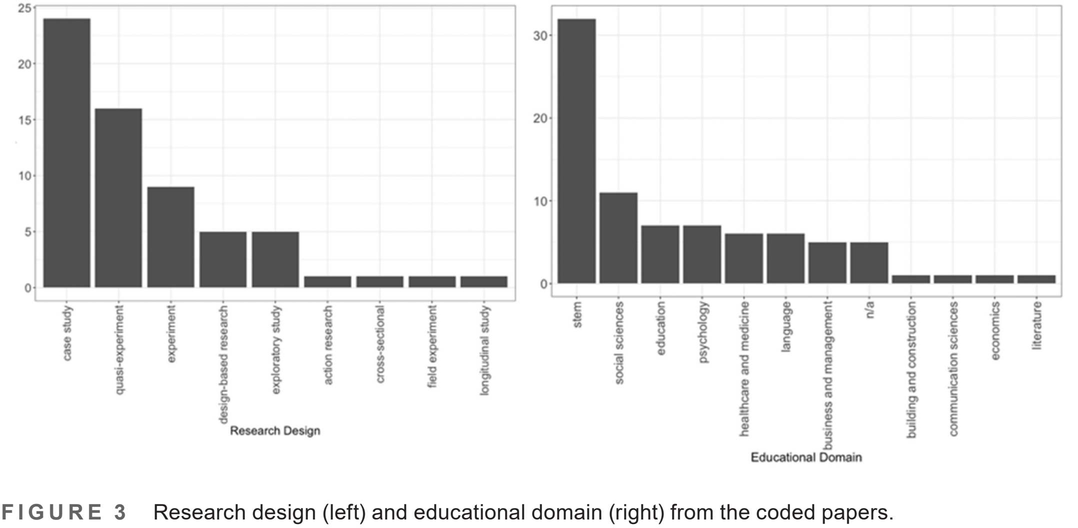

FIGURE 3 Research design (left) and educational domain (right) from the coded papers.

Concerning the learning environment used in the papers (Figure 4, left), 16 contributions used an LMS; 14 contributions used an online learning environment; eight papers used an ITS, whereas eight other papers used a CSCL environment; seven papers used self-developed tools; six papers used face-to-face classroom settings and two papers used a blended learning setting; while two others used conversational agents. Apart from this, one paper used a virtual reality system and one paper used a ubiquitous learning system. Four papers that did not specify the learning environment employed in the paper. Regarding the learning scenario (Figure 4, right), a clear majority (39) of the papers used a formal learning scenario, whereas 11 papers used non-formal learning scenarios and seven papers used an informal learning scenario. Three other studies did not explicitly mention the employed learning scenario.

When it comes to the educational levels of the learners involved in the studies (Figure 5, left), we observed that most (47 out of 59) of the studies had learners from university (40 undergraduate level, 3 graduate level, one master level, three did not mention the specific level in

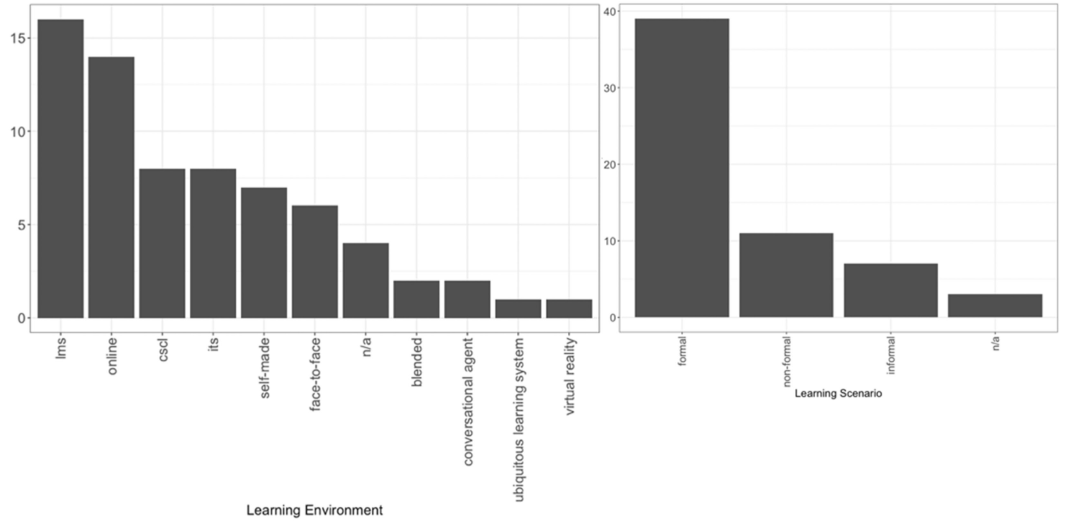

FIGURE 4 Learning environment (left) and learning scenario (right) from the coded papers.

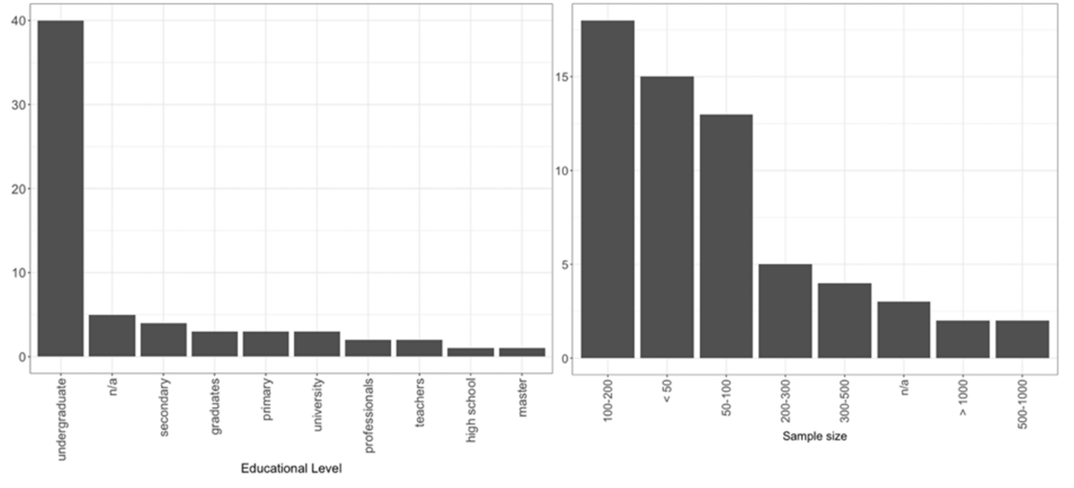

FIGURE 5 Educational level (left) and sample size (right) from the coded papers.

the university). Four papers employed learners from secondary schools; three papers had primary school children; two papers had professionals as learners; two other papers had trainee teachers and another had high school children as participants. Five other papers did not specify the educational level of the participating learners. Regarding the sample sizes reported in the papers (Figure 5, right), we observed that 18 papers had between 100 and 200 learners; 15 papers had <50 learners; 13 papers had between 50 and 100 learners; five papers reported a sample size between 200 and 300; four papers reported a sample size between 300 and 500; two papers reported a sample size between 500 and 1000; and two papers reported a sample size of more than 1000. Three papers did not mention the sample size.

We also conducted chi-square tests to find the dependence between the different dimensions of the educational context. We observed four significant dependencies among the six dimensions of educational context (ie, research design, educational domain, educational setting, learning scenario, population and sample size). First, we observe a significant dependency between research design and the educational domain ($\chi^2=96.07$, $p=0.004$). Regarding this dependency, there is a clear majority of two combinations: STEM domains and case-studies (11 studies) and STEM domains and quasi-experimental design (9 studies). Second, we observe a significant dependency between the educational setting and population ($\chi^2=155.23$, $p=0.00001$). There is a clear majority of two combinations: undergraduates and LMS (13 studies) and undergraduates and online setting (7 studies). Third, we observe a significant dependency between the learning setting and sampling size ($\chi^2=37.85$, $p=0.03$). The formal settings have between 50 and 200 students (23 studies out of 39 studies), and the non-formal settings have lower than 100 students in the studies (7 studies out of 11 studies). Finally, we observe a significant dependency between the population and sampling size ($\chi^2=141.41$, $p=0.00001$). Studies involving undergraduates have between 50 and 100 students (23 studies out of 39 studies) and studies involving graduates have fewer than 50 students (2 out of 2 studies).

Apart from the aforementioned observations from the direct coding process, we also mapped the educational domains and the educational levels of the participants reported in the papers with primary and secondary school children and trainee teachers, as participants are limited to STEM fields only. On the other hand, there is a decent distribution of the educational domains in the papers. The distribution of the educational domains in the papers employing university students as participants follows closely the distribution of the educational domains in this review. Further, we investigated which educational domains and educational levels were combined using informal learning scenarios. We observed that two studies that used informal settings were situated within social sciences and medicine respectively. While considering the educational levels of the studies employing informal scenarios, two had undergraduate learners and one had professionals as learners. Furthermore, we investigated the educational domains reported in combination with the school children (primary and secondary). We observed that four studies used STEM as the educational domain and one in the language learning domain.

Measurements used in the studies (RQ1b)

Next, we focus on the data collection and analysis reported in the papers included in this review. This includes the data collected, analysis type and the social units of analysis from the contribution. We observed that a wide variety of data collection instruments were used in the included papers (Figure 6, left). Many papers report using more than one type of data collected for their purpose of investigation. For example, 40 papers used some form of survey data; 24 papers used system-produced logs; 20 papers used performance tests; 11 papers used interviews; and nine papers used text written by students (written texts). Another set of

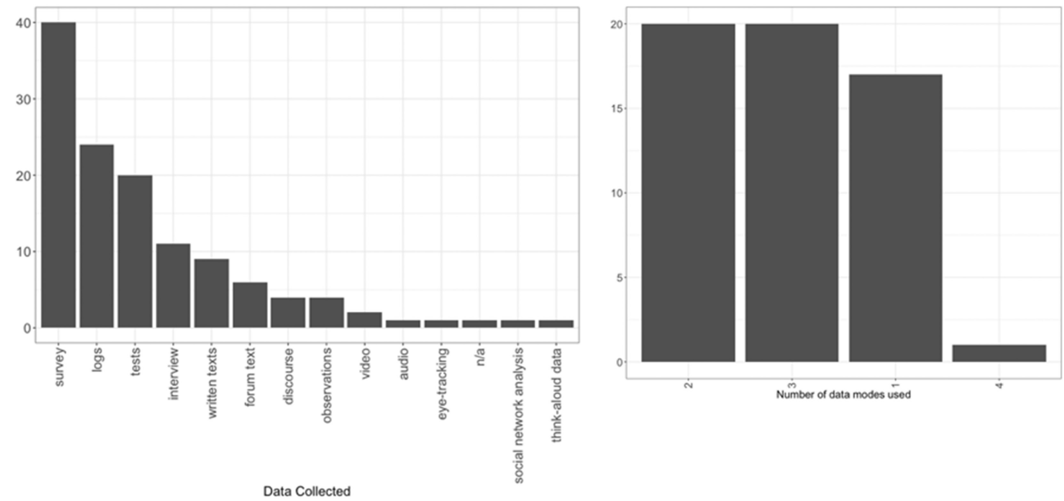

FIGURE 6 Data collected (left) and the number of data modes (right) from the coded papers.

six papers used forum text and two sets of four papers each used discourse and observations, while two papers used video data. Eye tracking, audio data and social network data were used by one paper each. There was only one paper that did not specify what sort of data they used. As we mentioned earlier, many researchers report using more than one type of data. As shown in (Figure 6, right), we observed that 20 papers used three modes of data; 20 other papers used two modes of data; 17 papers used only one mode of data and only one paper used four different types of data. Next, concerning the type of data analysis performed (Figure 7, left), we observe that 34 out of 59 papers used quantitative analysis while 18 papers used mixed method analysis. On the other hand, qualitative analyses were used in six papers each. Considering the unit of analysis reported in the papers (Figure 7, right), 41 papers focused on individuals, 12 papers focused on groups as their units of analysis and six papers focused on multi-level analysis.

Relation between the contextualisation and measurements (RQ1c)

In this section, we present the dependence between the educational contexts (ie, research design, educational domain, educational setting, learning scenario, population and sample size) and the measurements (ie, analysis unit, analysis type, number of data sources) used in the studies. We observe five significant dependencies. First, we observe a dependency between the research design and analysis methods ($\chi^2=42.57$, $p=0.003$). We observed that case studies, experiments and quasi-experiments used quantitative analysis (29 out of 34 studies), whereas case studies and quasi-experiments also used mixed methods (13 out of 17 studies). This can be explained by the tightly coupled nature of the research design approaches and data analysis methods. The inferential and statistical analysis methods are appropriate for experimental research design, while the case studies and quasi-experimental designs can also include certain qualitative analyses for triangulation purposes with the quantitative methods.

Second, we observed a significant dependency between learning scenarios and analysis methods ($\chi^2=21.71$, $p=0.009$). Formal learning scenarios are coupled with mixed methods and quantitative analysis (35 out of 39 studies), while non-formal learning scenarios are coupled with quantitative analysis (8 out of 11 studies). Assessing non-formal learning outcomes

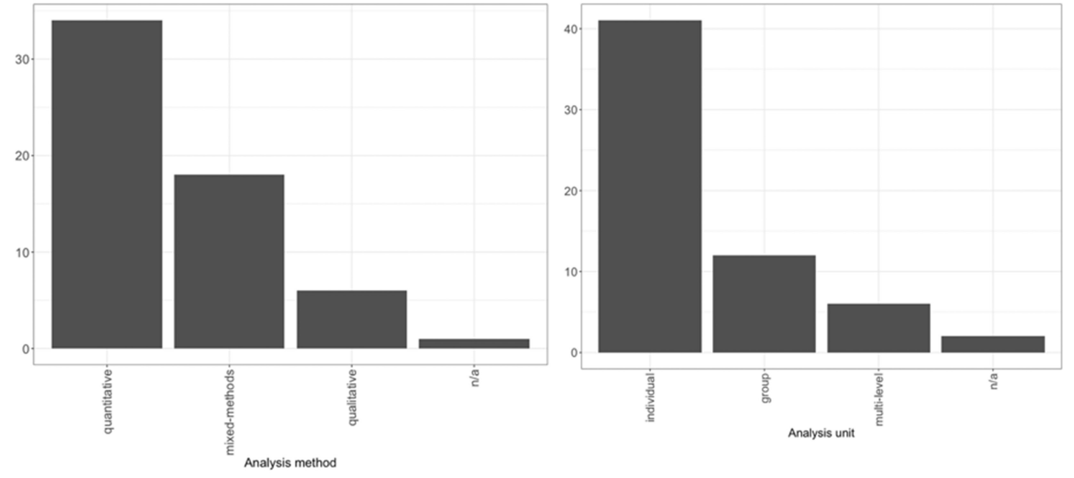

FIGURE 7 Analysis method (left) and analysis unit (right) from the coded papers.

can be challenging, as it often involves qualitative judgements about participants' progress, growth and development. These can be biased, and therefore, researchers might rely on self-assessments and surveys, resulting in more quantitative analysis approaches. On the other hand, acquiring reliable qualitative data is facilitated easily in the formal learning scenarios, making it suitable for mixed-methods analysis.

Third, we observe a significant dependency between the educational domain and the unit of analysis ($\chi^2=52.61$, $p=0.03$). Studies involving STEM topics have used individual levels of analysis (24 out of 30 studies), while studies involving healthcare and medicine have used group-level analysis (two out of four studies). There is also a bias from the educational context that could explain this dependency. STEM subjects are primarily taught in face-to-face classrooms, using an online course, or with an ITS. All these settings promote individual-level data collection and analysis. On the other hand, the educational practices in healthcare and medicine are mostly collaborative and group-based. Therefore, group-level analysis is also facilitated because of the educational context.

Fourth, we observe a significant dependency between learning scenarios and unit of analysis ($\chi^2=53.74$, $p=0.0001$). Studies involving formal scenarios have used the individual level of analysis (27 out of 39 studies) and group level analysis (nine out of 39 studies), while studies involving non-formal scenarios have used group levels analysis (six out of 11 studies) and multi-level analysis (three out of 11 studies). Similar to the third dependency, this can also be seen through the lens of the educational context; the nature of the formal scenarios facilitates the individual-level analysis because they are mostly set in a classroom, LMS, online or ITS settings, which inherently cater to individual educational needs. Meanwhile, the non-formal scenarios involved CSCL, self-developed technologies that inherently facilitated the group-level analysis. Therefore, we can conclude that the unit of analysis is mainly facilitated inherently from the learning setup and the technology used in the formal and non-formal scenarios.

Finally, we observe a significant dependency between learning scenarios and the number of data sources used ($\chi^2=32.96$, $p=0.0009$). Studies involving formal scenarios have used two (16 out of 39 studies) and three data sources (14 out of 39 studies), while studies involving non-formal scenarios have used one (four out of 11 studies) and three data sources (four out of 11 studies). We observed in these studies that in formal learning scenarios one of the data sources was system logs combined with certain physiological and/or audio/video. On the other hand, in the non-formal scenarios, the most common data sources were surveys which were combined with interviews and system logs, explaining either one or three data sources.

Research objective and outcomes reported in the studies (RQ2a)

Concerning the research objectives and the outcomes of the individual contributions, we present the seven themes emerging from our coding as a result of thematic analysis. It is important to observe that one contribution can be coded into more than one theme.

Feedback and scaffolding of the learning processes in ADLEs

This group of study focused on providing: (1) adaptive and personalized feedback to artefacts produced by students to help them achieve a better quality of artefact reduction (Saqr & López-Pernas, 2023; Wambsganss, Janson, Käser, et al., 2022; Wambsganss, Janson, & Leimeister, 2022; Wambsganss, Söllner, et al., 2022); (2) means for reflecting on their own learning behaviour (Akçapınar & Hasnine, 2022; Yilmaz et al., 2022); and (3) different adaptive and personalized scaffoldings to collaborative learning processes to foster better use of self-regulatory skills (Hadwin et al., 2018; Ouyang et al., 2023; Rienties et al., 2012). All these studies focused on improving a specific subset of SRL skills. For example, Wambsganss, Janson, Käser, et al. (2022), Wambsganss, Janson, and Leimeister (2022), and Wambsganss, Söllner, et al. (2022) provided feedback on students' texts to foster empathetic reviews, improve logical argumentation and build strong arguments. From the SRL standpoint, Wambsganss, Janson, Käser, et al. (2022), Wambsganss, Janson, and Leimeister (2022), and Wambsganss, Söllner, et al. (2022) showed that individualized feedback fosters self-monitoring and self-evaluation and social comparisons also trigger self-regulatory processes and lead to better outcomes. These findings are also supported by the results from Saqr and López-Pernas (2023) in collaborative learning settings. Furthermore, a learning analytic dashboard (Akçapınar & Hasnine, 2022) and monitoring learners' interactions within the learning environment (Yilmaz et al., 2022) could also be used to provide feedback to learners with low SRL skills. Other studies also report that personalized feedback on knowledge construction (Ouyang et al., 2023), motivational profiles (Rienties et al., 2012) and planning phases in collaborative settings also improved SRL skills. Another set of two studies used educational agents to scaffold team-based learning (Kumar, 2021) and learning-by-teaching (Lee et al., 2021). Kumar (2021) showed that an educational chatbot facilitated collaboration among team members and therefore improved the team performance. On the other hand, Lee et al. (2021) showed that a highly configurable design-facilitation tool can help students understand a large number of concepts. Finally, Rezaei et al. (2021) used a collaborative filtering method to provide one-on-one support to the learners and showed that such a method improves information flow and learning within the community.

Focusing on SRL/SSRL skills

This group of studies focused directly on SRL skills. For example, Isoc (2012) implemented a feedback structure that approached fundamental aspects of the professional practice of engineers, such as prioritizing the skills with responsible peer approval in a self-regulated manner. Similarly, providing opportunities for peer reflection also resulted in higher attainment of SRL skills (Michalsky & Schechter, 2013). Xia et al. (2023) also reported that the self-directed nature of SRL, which requires autonomy and effective engagement, could be supported by an artificial peer in the form of a chatbot. Other studies in this group examined the effects of specific interventions on SRL skills. For example, Daradoumis et al. (2021) created a tool to promote effort management and help-seeking, while Cheng et al. (2021) used a self-regulated flipped learning approach to cope with self-regulatory problems by guiding students to set their learning goals and supporting them in monitoring their learning status. Blau et al. (2017) also used a flipped class with a special emphasis on higher thinking skills from Bloom's taxonomy improves self-regulation and team co-regulation. Next, Wang et al. (2017) examined the use of adaptable collaborative scripts on SRL skills, resulting in improved metacognitive planning, while Lonergan et al. (2022) attempted to understand the role that project-based learning plays in improving self-regulatory skills and showed that progress in the PBL goals was correlated with the SRL skills. Moreover, Zheng et al. (2021) showed in a personalized collaborative environment that supporting collaborative knowledge building improves not only group performance but also the socially shared metacognitive regulation and cognitive load. In a similar view, Zheng et al. (2023) showed that supporting collaborative knowledge building and scaffolding the topic distribution improved socially shared regulation, and behavioural engagement in building knowledge. In another study, Zheng et al. (2023) showed that supporting collaborative knowledge building significantly improved coregulated behaviours, metacognitive learning engagement and social interaction.

Learning trajectories in ADLEs

Another set of contributions, concerns with identifying the different learning trajectories (paths, behaviour) in conjunction with SRL skills. Such contributions provided implications for adaptations to foster the acquisition and maintenance of SRL skills. Specifically, these contributions catered to individual learning (even if the studies were set up in collaborative contexts). For example, Jovanovic et al. (2017) and Zhu (2021) explored the learning trajectories within the flipped classroom setting and proposed that autonomy, provided in a flipped class, will directly affect learners' self-regulation behaviour in online learning. On the other hand, Cerezo et al. (2016) and Cheng and Xie (2021) explored the procrastination behaviour in LMS-related and online learning activities respectively. Both studies recommended that such behaviours are closely related to motivational aspects of SRL skills, while three other studies identified learning paths in online learning systems. Collectively these studies recommend appropriate levels of adaptiveness in the learning environment based on skill acquisition (Katuk et al., 2013), achievement goals (Sun & Xie, 2020) and affective processes (Gonzalez-Nucamendi et al., 2021) to promote SRL skills. Moreover, another set of studies proposed learning trajectory planning based on the learner profiles. For example, Shou et al. (2020) proposed planning to be done based on the analysis of collaborative learning behaviour, while Shi et al. (2014) proposed to use the learning profiles created within an e-learning system and Han (2023) proposed to use the demographics-based learning experiences to support the SRL processes in a blended learning environment.

Evolution of collaborative learning processes

Similar to the previous set of studies, this group of contributions focus on the evolution of collaborative learning processes in conjunction with SRL skills. For example, Ouyang et al. (2023) analysed multi-level characteristics (individual–group) of collaborative knowledge construction (CKC) and classified learner behaviours into CKC states, to enable personalized scaffolding opportunities. Within the same topic of CKC, Geng et al. (2021) used an online collaborative knowledge co-construction mechanism to facilitate student nurses' self-reflection on their performance and help student nurses. Harley et al. (2017) examined whether different levels of collaboration could be reliably identified and characterized between a learner and pedagogical agent to foster goal- and subgoal-setting in collaborative learning. Lin and Tsai (2016) used a group awareness tool to scaffold the learners to persist in training tasks and facilitating a learners' reflection of their learning status. Yilmaz and Karaoglan Yilmaz (2020) used a metacognitive group awareness tools to increase their awareness of the group and to contribute to the collaboration and improve their SRL skills. Finally, the last set of studies exploring collaborative mechanisms focused on teacher–student collaboration. For example, Inayat et al. (2013) revealed that collaborative practices, that is, group work, co-regulated team effort, timely feedback from instructors and consolidated support material enhances students' learning experiences. Moreover, Yang et al. (2023) observed the co-orchestration of the classroom and the authors discovered a potential tension between teachers' and students' preferred level of control, where students prefer a degree of control over the dynamic transitions that teachers are hesitant to grant.

Adaptation and regulation

This group of contributions focused on adaptive and regulating educational technology to help learners acquire and improve SRL skills. For example, Yadegaridehkordi et al. (2018) demonstrated that performance expectancy, social influence and personalization were the most important factors predicting behavioural intention to adopt cloud-based collaborative learning technology from experts' point of view; Yilmaz et al. (2022) designed a dynamic assessment process to support and test the learning competencies as well as the self-regulatory competencies. Larmuseau et al. (2018) used adaptation based on cognitive and motivational characteristics of students not only to provide certain learning tasks and practice but also to support the metacognitive awareness of learners. Chen et al. (2008) show that providing adaptive information to students improves not only the self-awareness but also the awareness of instructor's requirements. Wang et al. (2017) showed that sustainably adapting the collaborative script increases the students' engagement in metacognitive activities planning activities and the use of other self-regulatory processes. Moreover, Han et al. (2021) used learning analytics to develop a dashboard system that provided adaptive support for collaborative argumentation and showed that such an adaptive dashboard does not only improve the co-regulation but also the collaborative argumentation quality.

Self-assessment

Three other studies focused on students' self-assessment in relation to self-monitoring skills of self-regulatory behaviour. First, Stricker et al. (2011) show that learners who spent time with self-assessment tools performed better, and therefore, they recommended automatically adapting to users' knowledge skills and SRL competence levels. Second, Papamitsiou and Economides (2017) showed that the time spent on self-assessment tests and achievement behaviour correlates with goal expectancy and goal setting. Finally, Yilmaz et al. (2022) designed an intelligent tutoring system that identifies learners' learning needs through adaptive mastery learning and helps them monitor their assessment progress in a dynamic manner. Finally, Osifo (2019) showed that students reported high satisfaction when they were given the opportunity to choose activities and assessments according to their abilities and pace.

Understanding help-seeking behaviours in ADLEs

Only two studies focused on understanding health-seeking behaviours in conjunction with self-regulatory skills. The first was conducted by Puustinen et al. (2009), who showed that while asking for help, older students provided more context-related information than the younger students, indicating a higher level of metacognitive awareness in the older students. They further suggested that help systems or other supporting systems should consider the age of their users. The second study conducted by Shi et al. (2021), reported three different help-seeking modes: goal-directed, avoidant and exploratory; and suggested that help-seeking mode-based adaptation is necessary to scaffold the SRL skills.

SRL aspects of the studies (RQ2b)

In this section, we focus on the SRL aspects covered in the papers included in this review. The concerning codes include the concrete SRL aspects central to the theme of the papers, theoretical models used, SRL skills observed and how these skills were observed. When it comes to the central SRL aspects of the papers (Figure 8, left), we observed that 14 papers focused on metacognitive aspects; 14 papers focused on motivational aspects, another 14 papers focused on cognitive aspects; 12 people focused on metacognitive aspects; 9 papers focused on affective aspects. Finally, two papers focused on overall self-regulatory processes without specifying a concrete set or an individual aspect. There was only one paper where it was unclear, which was the central SRL aspect. Regarding the theoretical models used in the papers (Figure 8, right), we observed that a majority of papers have not clearly mentioned their theoretical basis (44 out of 59). Apart from that, eight papers used Zimmermann's model (Zimmerman, 1986), seven papers used Winne and Hadwin (2008), four papers used Bandura (1986), three papers used Pintrich (2000) and the other two used Winne (2013). On the other hand, the following models were used by one paper each: Boekaerts (1999), Efklides (2006), Elliot and Murayama (2008), Hadwin et al. (2011, 2017), Järvelä and Hadwin (2013), Pintrich and Zusho (2002), and Pintrich and de Groot (1990).

Considering the SRL skills' observation in the papers (Figure 9, left), once again, we notice that most papers do not have a concrete SRL skill (32 out of 59). Apart from that nine

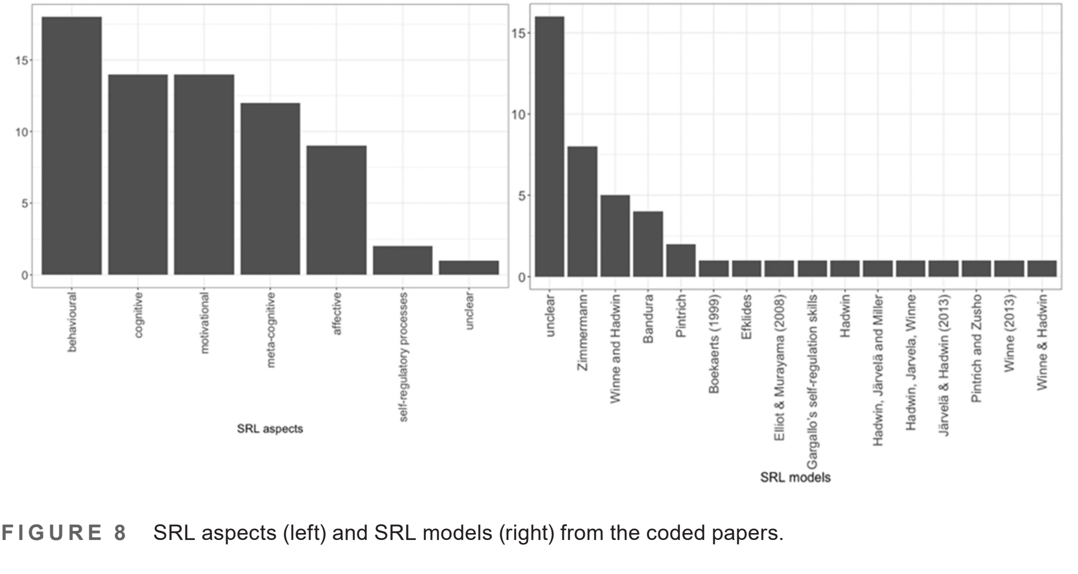

FIGURE 8 SRL aspects (left) and SRL models (right) from the coded papers.

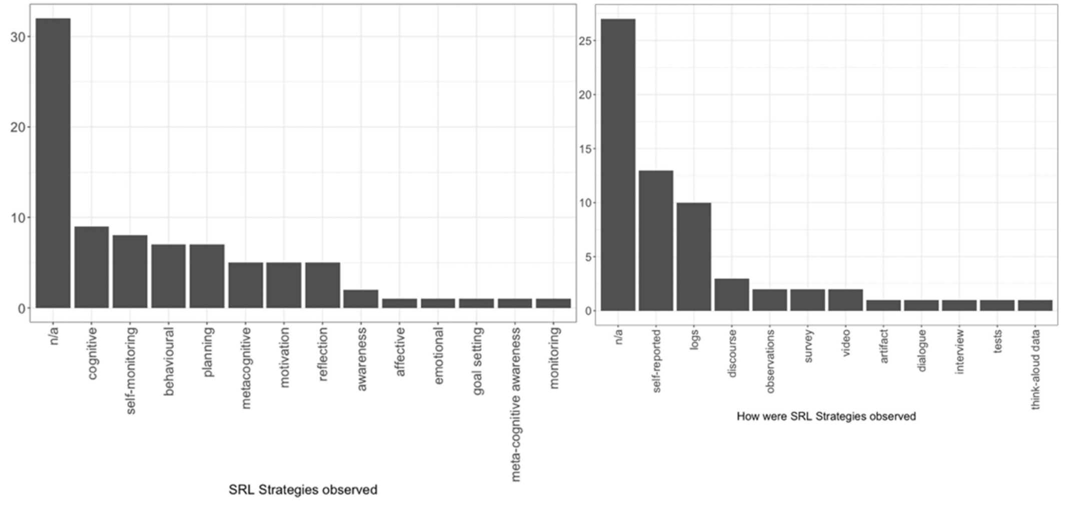

FIGURE 9 SRL skills observed (left) and how they were observed (right) from the coded papers.

papers focused on cognitive skills, eight papers focused on self-monitoring skills; planning and behavioural skills were central to seven papers each; metacognitive and motivational skills were central to five papers each. There were two papers which focused on awareness. Finally, the following skills were focused on by one paper each: affective skills, emotional, goal-setting, metacognitive awareness and monitoring. Among the papers that reported having observed concrete skills (Figure 9, right), 13 papers used self-reported data; ten papers used logs; three papers used discourse; two papers used surveys, two papers used videos and two papers used observations. Finally, the following data collection methods were used to observe the skills by one paper each: artefact, dialogue, interview, test and think-aloud.

SSRL aspects of the studies (RQ2b)

Finally, we will report on SSRL skills that were focused upon in the included contributions. This section includes the concrete skills, how these skills were observed and how the regulation was shared among peers in a group. We observe that a vast majority of papers do not focus on SSRL aspects covered (40 out of 59). Therefore, we will only report on the papers that have mentioned SSRL aspects. Among those papers, 14 focused on metacognitive aspects, eight focused on behavioural and seven focused on cognitive aspects. Moreover, emotional and motivational SSRL aspects were focused on by three papers each whereas, affective and co-regulation SSRL aspects were focused on by two papers each. We observe that a vast majority of papers do not focus on shared self-regulation (43 out of 59). Therefore, we will only report on the papers that have mentioned SSRL skills (Figure 10, left). Among such papers, six focused on metacognition, five focused on planning and four focused on behaviour. Cognitive, monitoring, reflection-based skills were observed by three papers each while emotional, motivational and sustained collaboration related skills were observed by two papers each. Finally, goal setting, metacognitive monitoring, organisation and task understanding related skills were observed by one paper each. To observe these skills (Figure 10, right) eight papers used discourse, six papers used system logs, another six papers used self-reported data, four papers used student-generated artefacts and interviews were used by three papers. The same data sources were also used to share the self-regulatory aspects (eg, behaviour, cognition and motivation) among the peers in the group.

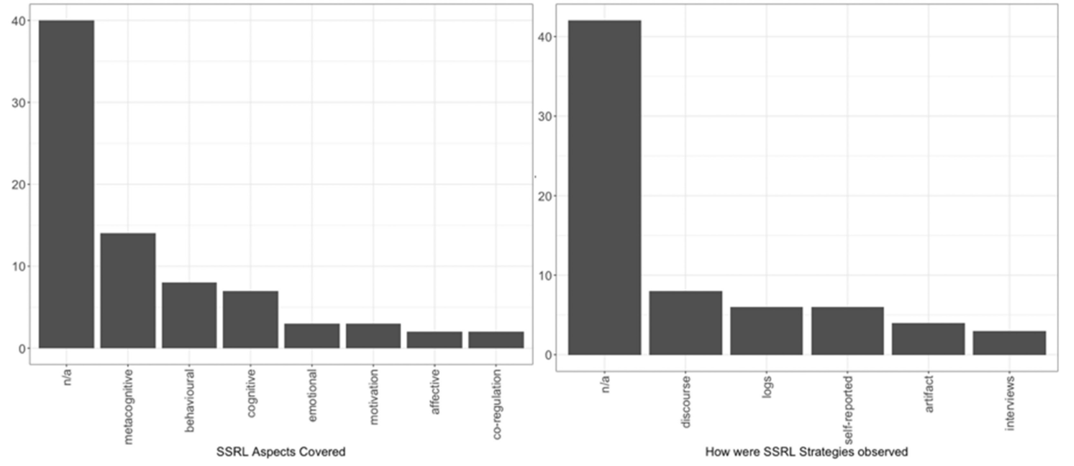

FIGURE 10 SSRL skills observed (left) and how they were observed (right) from the coded papers.

DISCUSSION

From the review of studies, where the focus is on scaffolding the learning processes in ADLEs, we observe that most of the research targeted the final artefact of the final learning outcomes. Although this was done via bringing about changes or improvements in the SRL and/or SSRL skills, the evaluation of those skills is missing from most of the contributions. By focusing on the overall learning outcomes and artefact through the scaffolding of the learning processes, the contributions showed improved quality of the artefacts and higher learning outcomes. However, whether the inherent processes were improved with the constant scaffolding remains unclear at large. For example, if a study aimed at improving the metacognitive awareness of the students through an adaptive solution and in turn improved students' learning outcomes, the analytical models show an improvement in the learning outcomes, but there is little emphasis on analysing the impact on the metacognitive awareness. Moreover, in such studies, it remains unclear whether it was actually the improvement of metacognitive awareness that resulted in the improvement of the learning outcomes. There has been a consistent push in the learning analytics and educational technology communities to analyse the process and process-based impact more (Csanadi et al., 2018; Sharma et al., 2020; Olsen et al., 2020), which is most prominently missing in the papers included in this SLR. In this SLR, there are only a few papers that address this issue. For example, Han et al. (2021) used learning analytics to show that the used adaptive dashboard does not only improve the co-regulation but also the collaborative argumentation quality.

From the studies that focus on the actual improvement of the SRL/SSRL skills using specific interventions such as chatbots and specially designed tools, we observe a lack of reporting on the generalizability of their findings. Although this is not necessarily the goal for many of these papers (eg, qualitative and exploratory works), it is advisable that such studies consider the confounds in their population when analysing learner data from a low (or medium) sample size within specific learning contexts. Most of the studies, while focusing on a given set of SRL/SSRL skills, created their own technology to emphasize the use of certain skills in a given context. The impact of the new intervention was also reported in the given context only without considering the confounds in the context. For example, if a study used adaptable collaboration scripts to improve SRL skills in a project-based learning context, it did not analyse what the effects of specific adaptations were on the different team compositions or how the reported results would transfer in other collaborative learning contexts. Similarly, if another study used a flipped classroom to examine the effects of their interventions, it did not analyse what the effects could be in another classroom setting. Missing such transfer-related analytical approaches might result in the unsustainable use of technology in many cases (Ringstaff & Kelley, 2002).

Through this review, we also observe that only three studies focused on the self-assessment process. Further, only two studies focused on help-seeking behaviour. Both of these processes are highly important to both learning and self-regulated learning. In self-assessment, students reflect on their learning process, strengths, weaknesses and areas for improvement. Metacognition and deeper understanding are fostered by this reflective practice (Yan, 2020). Students take ownership of their learning journey when they assess their own progress and performance. Ownership increases motivation and engagement, resulting in better results. Self-assessment allows students to identify their own learning gaps and misconceptions. As a result of this awareness, they can seek out additional resources or assistance where needed (Tailab & Marsh, 2020). SRL also requires setting goals. Students can set realistic and meaningful goals based on their understanding of their current abilities and desired outcomes through self-assessment (Chung et al., 2021).

On the other hand, students' ability to monitor, control and adapt their learning strategies to achieve academic success is supported by help-seeking behaviour and self-regulated learning (Puustinen et al., 2009; Shi et al., 2021). In order to empower students to become proactive, independent learners who take responsibility for their learning journey, educators can foster both help-seeking behaviour and self-regulated learning skills. Another missing feature from the studies and the contributions in this SLR is the lack of focus on self-assessment and help-seeking behaviour.

In the remainder of this section, we will present the salient features of this systematic literature review and we also provide certain interpretations of those features based on theoretical and practical knowledge from the field of adaptive learning, educational psychology, learning technologies and learning analytics. We divide the salient features into two groups. The first group represents the state-of-the-art, while the second group represents the challenges and opportunities in the field.

Overall state-of-the-art

High-level reporting detail

We observed that all the 59 papers included in this systematic review maintain a high level of detail reporting about the study context, procedure, participants, research objectives and theoretical foundations. Although we noticed some of the information was missing from a small set of papers, there was no significant impact on the coding quality. Moreover, there was not a single paper where more than one aspect of reporting the details was missing; this goes in line with some of the other systematic reviews done in the field of SRL and ADLEs (eg, Alajlani et al., 2023; Alzahrani et al., 2020; Heikkinen et al., 2023).

Heavy reliance on STEM domains

While preparing the codes for the context of the studies reported in the contributions included in this review, we reported that a majority of papers were situated within STEM domains (32 out of 59 papers, Figure 2, left panel). One plausible explanation for this fact roots from the structure of STEM subjects. We know that these subjects have a more formalized structure of the content than the other domains and these subjects are also easier to make competency maps for (that is especially important in adaptive technologies) than the other domains (Reinholz et al., 2021; Sánchez Carracedo et al., 2018). This encourages the researchers to rely on STEM subjects for developing adaptive technologies and using those technologies to explore and understand the self-regulatory behaviour of students.

Strong ties within schools and STEM

In line with the previous salient feature of heavy reliance on the STEM domains, we also observe that most studies conducted within primary and secondary educational levels were also concerned with STEM subjects (4 out of 5 papers). The main reason for such an observation could be similar to the heavy reliance on such subjects but it could also be the case that it is easier to foster self-regulatory behaviour in adults than children (Whitebread et al., 2009) as some writers have argued that it is a late developing capability (see the review from Veenman et al., 2006). Therefore, having an educational domain that is easier to draw competency maps for would certainly aid researchers in carrying out the explorations in primary and secondary education levels.

The majority of studies focused on higher education

We also observed that most of the studies concerned learners from the university (47 out of 59 papers). As we mentioned in the previous salient feature that self-regulatory skills are considered to develop later in the developmental process (Veenman et al., 2006; Whitebread et al., 2009), the same reason could also explain why there are a majority of studies, included in this literature review, focused on higher education. Another possible explanation for this could be rooted in the computer self-efficacy differences between children and adults. Studies have shown that there are a considerable computer self-efficacy differences between children and adults (Chu, 2010; Huang, 2013; Vierhaus et al., 2011), and most of the environments used in the papers included in this review employed technology; therefore, using university students as the participating learners in such studies keeps the research design focused and straightforward.

Good coverage of the SRL aspects

Finally, we observe that the comprehensive coverage of SRL aspects in the reviewed papers is commendable and highlights the multifaceted nature of SRL. The papers clearly focused on self-monitoring, goal setting, planning, reflection and metacognitive activities. However, there is a difference in the level of focus among the 59 papers; some focus on specific SRL activities/processes, while others focus on the overall SRL process. A notable observation from the results is the balanced emphasis on the four primary aspects in SRL, specified as cognition (14 papers), affect (9 papers), metacognition (14 papers) and motivation (14 papers) (CAMM) processes. This balance indicates an evolving understanding of the complex interplay between these components in the learning process (Azevedo, 2015; Järvelä, Nguyen, & Hadwin, 2023). We also observed that 19 of the 59 papers focus on more than one self-regulatory aspect fitting the adaptive educational technology. This multifaceted approach is crucial for developing ADLEs that can cater to individual learner needs by considering various SRL aspects. This approach resonates with the trend towards personalized learning, where technology adapts to learners' unique cognitive, affective, metacognitive and motivational profiles (Nguyen et al., 2023, 2024).

Challenges and opportunities

Limited use of informal settings

One of the key observations from coding the 59 papers was that only seven studies focused on informal learning settings. One plausible explanation is that informal learning spaces are created for a specific purpose (Berman, 2020). Integrating the ADLEs into the informal learning spaces presents its challenges because there has to be a seamless integration between the informal learning space and the ADLEs to foster the acquisition of self-regulatory skills within the informal learning space. Lane (2014) and Bartle (2015) have mentioned certain challenges of integrating ADLEs or other learning technologies within the informal learning space in a seamless manner. However, these challenges also presented an opportunity for researchers in both educational technology and human–computer interaction fields to explore different ways of such seamless integration.

Lack of theoretical convergence and clarity over the theoretical models

The concept of SRL has been framed through several theoretical lenses, with seminal works from Zimmerman and Moylan (2009), Pintrich (2000) and Winne and Hadwin (1998), among others. While these models share the common idea of learners actively controlling their learning processes, they differ in terms of the specific mechanisms and phases of SRL emphasized. This lack of theoretical convergence can lead to inconsistencies in how SRL is conceptualized, measured and promoted in educational practice. The challenge is even more prominent for SSRL, which is a relatively new construct. Current theories draw heavily on SRL models but adapt them to a collaborative learning context. This adaptation necessitates acknowledging the collective nature of regulatory activities within group contexts, alongside the intricate interplay between individual and shared regulatory (SSRL) processes (Hadwin et al., 2017). However, a unified model of SSRL is yet to be established, leading to a lack of clarity in defining, assessing and fostering SSRL (Järvelä, Nguyen, Vuorenmaa, et al., 2023). Lack of theoretical convergence and clarity can impede the empirical investigation of (S)SRL and the development of evidence-based interventions. Therefore, future research should aim to bridge the gaps between different theoretical models and develop a comprehensive, unified framework of (S)SRL that captures both individual and collective aspects of regulation in learning.

Lack of concrete SRL monitoring skills

For SRL, while there is a consensus that it plays a crucial role in academic success, there is also an ongoing debate about the effectiveness of skill monitoring and application. One common issue is that many learners may know about SRL skills but struggle to monitor and apply them effectively (Dignath et al., 2008). These challenges can stem from learners' insufficient metacognitive skills to effectively monitor and adapt their learning strategies (Schraw & Dennison, 1994). Also, many educational interventions often introduce learners to SRL skills without adequately equipping them with the tools needed for effective monitoring and adjustments (Dignath & Büttner, 2008). While substantial progress has been made in understanding SRL, less attention has been paid to SSRL. There is a scarcity of valid and reliable measures to assess SSRL, as monitoring SSRL skills in practice also presents challenges. One issue is the difficulty in tracking and assessing how well regulatory activities are distributed and coordinated within a group (Hadwin et al., 2017). Traditional self-reported measures used in SRL research are insufficient to capture the dynamic, interactive nature of SSRL and observational methods can be time-consuming and subjective (Järvelä & Hadwin, 2013). Another challenge lies in managing and balancing individual and shared regulatory processes. In group settings, individual members might not accurately perceive or may neglect others' regulatory contributions, leading to suboptimal collaboration (Järvelä & Hadwin, 2013). The development of digital collaborative learning environments, while providing opportunities for improved monitoring, also needs careful design to support and visualize SSRL processes effectively (Järvelä et al., 2016). Therefore, further research and advancements in educational technology are needed to better support and enhance the monitoring and application of both SRL and SSRL skills.

The use of multimodal data is limited

Two-thirds of the papers used more than one type of data. However, most studies were limited to surveys, system logs, tests, online discussions, interviews, written text and observations. With the current advancements in multimodal learning analytics (Sharma & Giannakos, 2020) and sensing technologies (Giannakos et al., 2022), it has become easier to use more than system logs and text-based data to analyse learning processes. We argue that by not using sensing technologies and multimodal data, the researchers are limited to self-reported data and system logs that do not present factual-real-time information about the learning processes (Ginnakos et al., 2019; Lee-Cultura et al., 2022). By using sensor-based analytics, one can develop a deeper understanding of SRL processes, as it has been shown in other subdomains of learning analytics (Järvelä, Nguyen, Vuorenmaa, et al., 2023). Recent studies show that applying multimodal data to monitor and understand (S)SRL skills offers significant potential. Traditional assessment methods often fail to capture the dynamic and complex nature of (S)SRL processes. Multimodal data, which includes various sources like digital learning environments' interaction logs, physiological data (eg, eye-tracking) and natural language processing of learners' reflections, offers a promising solution. This approach provides a more fine-grained and objective understanding of learners' regulation processes and skills and their interaction in social learning contexts (Azevedo et al., 2019; Hadwin et al., 2017). Therefore, despite the challenges related to data analysis and privacy concerns, leveraging multimodal data for (S)SRL monitoring can revolutionize our understanding of these complex learning processes and pave the way for more effective, personalized educational interventions.

Use of AI/XAI is limited

We observed that only 4 out of 59 papers used AI/agents (Harley et al., 2017; Kumar, 2021; Lee et al., 2021; Xia et al., 2023). The field of AI has seen a tremendous increase in the quality of conversational agents and intelligent agents (Borsci et al., 2022; Radziwill & Benton, 2017; Ruane et al., 2018), which can provide a better interactive experience than simple system prompts. This presents a unique opportunity for educational technology developers who design and develop adaptive technologies. Using high-quality conversational agents and other intelligent agents one can provide better scaffolding to the SRL processes of the learners. Furthermore, the field of AI has also seen advancements in explainable AI methods (Nauta et al., 2022) which indicates that the inner processes of conversational agents might no longer remain a black box to educators, practitioners and learners. This provides a unique opportunity for educational technology researchers to open the adaptive models to the end users so that their acceptability can be increased.

Limitations

Regarding limitations, the authors of this study had to make some methodological decisions (eg, the choice of databases and the search query) that might introduce certain biases into the results that need to be accounted for. However, we did our best to avoid such biases by considering all the major databases and following the steps outlined by Kitchenham and Charters (2007). The second bias may be attributed to the selection of empirical studies and the coding of the papers in the papers themselves. It should be noted that the focus was clearly on the empirical evidence and the papers were coded by three independent researchers who worked independently from each other. It has also been found that some elements of the papers were not accurately described, resulting in some missing information in the coding of the papers. The amount of missing information was minimal and the results would not be affected significantly by the small amount of missing information.

Conclusion

ADLEs within the collaborative learning paradigm have been presented in the form of a set of 59 contributions from the last 23 years with a focus on SRL/SSRL. We analysed the papers from the perspective of the study design (learning context, learning environment, population and so on) and based on the insights they provided regarding learners' performance/outcome or behaviour from the perspective of SRL/SSRL in ADLEs, based on the study design. There were various challenges and opportunities that emerged from the current review in terms of both the method used and the impact it might have on our understanding of learners' SRL and/or SSRL skills/knowledge as a result of categorizing the main findings of the selected papers into the seven thematic areas. Last but not least, based on the field's current state, we have proposed some additional possible advancements that could be considered.

CONFLICT OF INTEREST STATEMENT

None of the authors have any conflicts of interest with respect to the current contribution.

FUNDING INFORMATION

None.

DATA AVAILABILITY STATEMENT

The coding of the papers could be obtained from the corresponding author.

ETHICS APPROVAL STATEMENT

None.

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ENDNOTE

[1] https://rm.coe.int/1680459f97

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APPENDIX A: PAPERS INCLUDED IN THE FINAL CODING

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Sharma, K., Nguyen, A., & Hong, Y. (2024). Self-regulation and shared regulation in collaborative learning in adaptive digital learning environments: A systematic review of empirical studies. *British Journal of Educational Technology*, *00*, 1–39. https://doi.org/10.1111/bjet.13459