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## SYSTEMATIC REVIEW OF SELF-REGULATED LEARNING INTERVENTION AND MEASUREMENT IN HIGHER EDUCATION: TOWARDS A HOLISTIC, INTEGRATED, AND TECHNOLOGY-ASSISTED MODEL

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### ABSTRACT

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Aim/Purpose	This study aims to analyze self-regulated learning interventions and measurement approaches in higher education as an initial contribution towards a model for holistic, integrated, and technology-assisted self-regulated learning support.
Background	Previous reviews lacked insight into how to combine self-regulated learning interventions and measurements. It is essential to understand these interventions, measurements, trends, and relationships to develop a holistic, integrated, and technology-assisted model to support self-regulated learning in higher education.
Methodology	This systematic literature review was conducted in accordance with the guidelines provided by Kitchenham and Charters for systematic literature reviews in software engineering. A total of 109 studies on self-regulated learning in higher education published between 2014 and 2023 were selected and reviewed. Data

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extraction on self-regulated learning interventions and measurements used by those studies was conducted. Qualitative content analysis of interventions and measurements was performed using provisional coding to produce categories, and the Jaccard Index was employed to assess the associations between these categories. Interventions were categorized into six groups: planning-based, reflection-based, training-based, prompt-based, feedback/report-based, and technology-assisted interventions. Similarly, measurements were classified into seven groups: quantitative questionnaires, qualitative questionnaires, interviews, focus group discussions, think-aloud protocols, information system data, and assessment data.

Contribution	This review examines recent trends in self-regulated learning interventions, measurements, and their interconnections in higher education. These trends inform support strategies and provide guidance to teachers, instructional designers, and decision-makers regarding self-regulated learning practices. We propose an initial model for a holistic, technology-assisted approach to supporting self-regulated learning, which should be further validated by higher education stakeholders prior to implementation. Our recommendations include training in self-regulated learning, designing instruction to foster these activities, providing suitable tools, and leveraging usage data for event-based measurement.
Findings	Identified interventions include planning-based, reflection-based, training-based, prompt-based, feedback/report-based, and technology-assisted approaches. Technology-assisted interventions are often combined with other methods, and feedback or report-based interventions frequently occur alongside technology-assisted ones. The most common measurements are self-reported quantitative questionnaires and assessment data. System logs are increasingly used to measure self-regulated learning by capturing events, while self-reports evaluate aptitude. Qualitative data, such as interviews and focus groups, are used less frequently. Notably, there is a strong association between technology-assisted interventions and the use of system logs for measurement purposes.
Recommendations for Practitioners	Higher education institutions should conduct training programs to equip teachers with the skills needed to support students' self-regulated learning. Teachers can prompt students to use self-regulated learning strategies. Various tools, such as learning management systems and learning analytics dashboards, can aid in fostering self-regulated learning. Data from these tools can be analyzed using educational data mining approaches to provide actionable insights for both overall learning activities and data-driven feedback for students.
Recommendations for Researchers	Future research should prioritize validating the proposed model with qualitative methods and expert feedback to improve its accuracy. Create integrated measurement dashboard systems that provide students and teachers with actionable insights into self-regulated learning processes and instructional design.
Impact on Society	By encouraging self-regulated learning, this model can potentially enhance academic performance, improve learning outcomes, and equip students with the essential skills necessary for lifelong learning and success in a rapidly changing world.
Future Research	Future research will focus on validating the initial model through qualitative methods, gathering real-world insights from teachers via interviews or focus groups, and developing an integrated measurement dashboard system.

Keywords self-regulated learning in higher education, learning analytics, learning design, technology-assisted intervention, systematic review, holistic and integrated model, learning traces, system logs

## INTRODUCTION

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In higher education, students are expected to learn independently rather than being taught (Vosniadou, 2020). To succeed, they need effective learning strategies and the ability to find information through technology (Biddix et al., 2011). These skills became essential when learning shifted online during the COVID-19 pandemic (Nan Cenka et al., 2023). In online classes, students often work independently and asynchronously, which requires them to locate resources and complete assignments, affecting their course performance (Kim et al., 2018). However, many students struggle because they lack practical learning skills (Morelli et al., 2023). The COVID-19 pandemic highlighted the significance of self-directed learning (Nan Cenka et al., 2023). Despite this, higher education institutions typically rely solely on grades to measure student success in a “one-size-fits-all” manner, which has numerous limitations in providing insights for improving learning and learning design (Cachia et al., 2018; Schwab et al., 2018).

Self-regulated learning (SRL) is crucial for developing independent learners, involving motivation, actions, and thinking (Zimmerman & Pons, 1986). Various SRL models exist, describing different stages of learning. They generally follow three key phases: the preparatory or forethought phase, which includes activities like interpreting the task and setting goals; the performance phase, involving doing, controlling, and monitoring the task; and the appraisal phase, which covers evaluation and self-reflection (Panadero, 2017; Zimmerman, 2000). Additionally, researchers have created tools to measure SRL, such as self-report questionnaires like the Motivated Strategies for Learning Questionnaire, or by analyzing SRL processes through learning traces (Pintrich & De Groot, 1990; Winne & Perry, 2000).

Supporting SRL involves several key aspects. Since SRL is dynamic and context-dependent, interventions and assessments must be integrated (Butler & Cartier, 2005; De Corte et al., 2004). Interventions can include training in SRL techniques (Theobald, 2021), self-monitoring tools (Pérez-Sanagustín et al., 2022), and technology-based solutions (Radović & Seidel, 2025). Assessments range from self-report questionnaires to analyzing learning activity data (Winne & Perry, 2000). Teachers and learners play distinct roles: teachers scaffold SRL strategies while learners actively apply them (Dülger et al., 2025; Kramarski, 2017). Additionally, technology can enhance the effectiveness of SRL support (Radović & Seidel, 2025). In summary, these three aspects – a holistic involvement of teachers and students, integrating interventions and assessments, and utilizing technological tools – can enhance SRL support.

Several studies have explored different aspects of SRL, but few have examined all three aspects together. For example, Alvi and Gillies (2020) focus on core SRL elements but leave out the role of technology from teachers’ perspectives. They state that SRL support relies on teachers’ beliefs and institutional support but overlook practical issues such as a lack of time and resources, as noted by Faza and Lestari (2025). Institutions may also be more focused on pass rates rather than supporting SRL (Agbenyegah & Geduld, 2024). To address these challenges, technology could be used as a direct support for students (e.g., electronic learning diaries, reflection tools, and adaptive recommendations) and as an indirect support by providing teachers or institutions with data-driven insights on students’ SRL (Dülger et al., 2025; Radović & Seidel, 2025). Some models explaining the role of technology in supporting SRL mainly concentrate on technical aspects, such as educational data mining, without considering traditional methods (e.g., Araka et al., 2019, 2022). Understanding how technology fits within traditional teaching and learning approaches is essential for integrating it effectively. Therefore, there is an opportunity to develop comprehensive models of technological support that involve both teachers and students to promote sustainable SRL support in higher education.

To develop such models, insights must be gathered for each aspect of the problem. For the holistic involvement aspect, Alvi and Gillies (2020) have already discussed it at a high level. Practical actions can be further explored through real-world observations or qualitative studies. Insights on integrating interventions, measurements, and the role of technology can be initially drawn from prior empirical studies, as testing interventions with specific measurements is a common practice in the field. Previous reviews have examined SRL interventions or measurements but often focus on either one or neglect the connection between them (e.g., Araka et al., 2020; Heikkinen et al., 2023; Wong et al., 2019). Additionally, many reviews have not addressed the potential for integrating strategies, the role of technology, or are limited to specific intervention types or environments (e.g., Araka et al., 2020; Heikkinen et al., 2023; Nan Cenka et al., 2022; Pérez-Álvarez et al., 2018; Theobald, 2021). This review aims to fill that gap by exploring the connection between interventions and measurements, as well as the role of technology, serving as a step toward a holistic, integrated, and technology-supported SRL framework in higher education.

Several review questions guided this systematic literature review, as outlined below:

- RQ1.** What trends are present in SRL interventions, both technology-assisted and non-technology-assisted, within the context of higher education?
- RQ2.** What trends are present in the measurement of SRL within the context of higher education?
- RQ3.** How do the identified trends in SRL interventions and measurements relate to one another in prior studies?

## LITERATURE REVIEW

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### *SELF-REGULATED LEARNING MODEL, INTERVENTIONS, AND MEASUREMENTS*

Self-regulated learning (SRL) involves cognitive, emotional, and strategic elements that influence how people learn (Panadero, 2017; Schunk & Greene, 2018). It aligns thoughts, feelings, and actions toward learning goals, going beyond simple strategies to include cognitive awareness (Flavell, 1979; Pintrich & De Groot, 1990; Zimmerman, 1986). Several SRL models exist, such as Zimmerman's (2000) cyclical process model, Boekaerts' (1991) dual appraisal process model, Pintrich's (2000) model emphasizing SRL and motivation, Efklides' (2011) metacognitive and affective SRL framework, Winne and Hadwin's (1998) multi-stage, multi-facet model, and Järvelä et al.'s (2016) socially shared regulation model. These models offer different perspectives, such as the phases of forethought, performance, and self-reflection in Zimmerman's model, or the dual-process approach, which emphasizes both learning and emotional factors, in Boekaerts' model. Panadero (2017) reviewed these models and identified typical phases, including preparatory, performance, and appraisal. However, each model focuses on different aspects; for example, Winne and Hadwin's and Efklides' models emphasize cognitive factors, while Zimmerman's and Pintrich's highlight motivation, and Boekaerts emphasizes emotion. These differences shape the understanding of SRL and its crucial role in education.

Butler and Cartier (2005) viewed SRL as an adaptive process, similar to Winne and Hadwin's (1998) model. Their model presents SRL as an ongoing process of knowledge development with six dimensions: context, student characteristics, mediating factors, SRL strategies, personal goals, and cognitive strategies. Context includes geographic, institutional, curricular, and subject areas. Butler and Cartier (2005) illustrate this dimension with examples, such as differences in socio-political conditions that can influence educational settings and policies, which can also indirectly impact students' SRL, highlighting the cross-cultural aspects of SRL. Some empirical studies also support the idea that socio-cultural factors can shape students' traits, suggesting that SRL models should be adapted or modified to fit specific socio-cultural contexts (Sappor, 2022; Tong et al., 2020). They also note that student characteristics or individual traits are a dimension explaining what individuals bring to different settings. Mediating factors include background knowledge, perceptions, ideas, and emotions related to

learning. SRL strategies involve task interpretation, planning, monitoring, evaluation, and adjustments, while personal goals refer to an individual's specific objectives. Cognitive strategies involve learning methods like note-taking and practice. Besides Butler and Cartier's model, Alvi and Gillies (2020) synthesize contextual SRL from the perspectives of teachers and the learning environment, rather than focusing solely on SRL components or strategies. This model emphasizes teachers' role as the primary agents of SRL improvement within microsystems, such as classrooms or course-level settings. Meanwhile, on the macro system, both organizational culture and curricular support are crucial.

Since multiple researchers – conceptually (e.g., Schunk & Greene, 2018), empirically (e.g., Higgins et al., 2023; L. Xu et al., 2022), and through systematic literature review and meta-analysis (e.g., Caixia et al., 2025; Cheng et al., 2025; Jansen et al., 2019) – assert and support the idea that SRL skills, even though their effects can be small, moderate, high, or mixed, and may be direct or mediated, have a positive relationship with academic performance, it would be beneficial for educators and educational institutions to focus on improving this skill. Alvi and Gillies (2020) propose in their model that SRL support should consider who should be involved in the strategy and in what context it is provided. Consistent with this, Kramarski (2017) emphasizes that teachers are the primary agents of students' SRL because they act as facilitators and serve as SRL role models. Effective SRL-supporting teachers should possess both content knowledge and pedagogical content knowledge of SRL, and their motivation and self-efficacy in promoting SRL are crucial (Karlen et al., 2020).

There are several ways to support students' SRL skills. Earlier research suggests that SRL can be enhanced through specialized training for both teachers and students (Porter & Peters-Burton, 2021), as well as through tools such as to-do lists and learning diaries (Eilam & Aharon, 2003; Zarei Hajjabad et al., 2022). Clearly communicating learning outcome expectations also supports student SRL (Habib et al., 2021; Panadero et al., 2012). Achieving this requires teachers to take the lead as the main agents. However, implementing these strategies on a broad scale can be difficult due to differences in teacher competence, limited time, and support from institutions and technology (Agbenyegah & Geduld, 2024; Faza & Lestari, 2025). Institutional backing is essential, and technology has the potential to address these challenges within learning environments (Alvi & Gillies, 2020; Radović & Seidel, 2025).

There are several ways in which technology can support SRL. From a broader perspective, Faza and Lestari (2025) mention several tools that could support SRL, such as learning management systems (LMSs), massive open online courses (MOOCs), artificial intelligence and chatbots, and collaborative platforms. These technologies are not explicitly linked to SRL; rather, they enable students to regulate their own learning. Some technologies are specifically designed or consider SRL in their development. For example, Radović and Seidel (2025) mention some examples, including learning analytics dashboards (LADs), adaptive recommendations and feedback, and tools for goal-setting, self-assessment, and reflection.

Besides interventions to support SRL, some research focuses more on measurement. SRL can be evaluated through various methods depending on the perspective (Winne & Perry, 2000). When viewed as an ability, self-report questionnaires or interviews can assess learners' understanding and perceptions of their learning behaviors. Self-report questionnaires contain statements that learners respond to, usually on a rating scale. Examples include the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993), the Learning and Study Strategies Inventory (Weinstein et al., 1988), and the Online SRL Questionnaire (Barnard et al., 2009). Although questionnaires are easy to administer, they might lack depth. Structured interviews, like the SRL Interview Schedule (Zimmerman & Pons, 1986), can help address this issue.

Alternatively, SRL can be seen as an event (Winne & Perry, 2000). This method emphasizes observable actions during learning rather than internal perceptions. Think-aloud protocols, where learners vocalize their thought processes, can be employed. Analyzing traces of learning activity provides an

additional assessment approach (Winne & Perry, 2000). These traces, such as reading or note-taking, can be mapped onto SRL theory. Advances in technology have made it possible to log these traces in learning environments, enabling analysis through learning analytics or educational data mining. Frameworks like Trace-SRL support the use of trace data from system event logs to understand SRL processes, offering insights into behavioral and temporal aspects (Saint et al., 2020).

### ***TOWARDS A HOLISTIC, INTEGRATED, AND TECHNOLOGY-ASSISTED SELF-REGULATED LEARNING SUPPORT MODEL***

Aligning with prior research that emphasizes the importance of the teacher’s role in supporting SRL, intervention strategies should holistically involve both teachers and students (Jud et al., 2024; Karlen et al., 2020; Kramarski, 2017). Furthermore, like other competencies, support through interventions and assessment via measurements is crucial and closely linked, especially for establishing SRL as a key performance indicator and embedding it within higher education institution cultures in the long term (De Corte, 2016, 2019; De Corte et al., 2004). Technology can contribute to creating an environment conducive to SRL by directly enhancing efficiency and providing data-driven support for SRL, even when teachers face time and competency limitations (Agbenyegah & Geduld, 2024; Radović & Seidel, 2025). Based on these three potential aspects of supporting SRL, the future goal of this research is to construct a support model characterized by its holistic involvement of both teachers and students, integrated intervention and measurement approaches, and assistance from technology. While creating such a model requires insights from experts and stakeholders, especially to validate the holistic aspect of our proposed model, this study serves as a preliminary endeavor, mainly to identify patterns of intervention and measurement and to identify factors that are already assisted by technology.

### ***PREVIOUS REVIEWS***

Previous reviews have explored various aspects of SRL, such as tools for online learning (Pérez-Álvarez et al., 2018), massive open online courses (Wong et al., 2019), personal learning environments (Nan Cenka et al., 2022), and learning analytics interventions (Heikkinen et al., 2023). There is also a review that lists technology supporting SRL (Faza & Lestari, 2025). However, as shown in Table 1, none have specifically addressed the need for a comprehensive, integrated model, nor have they discussed the relationship or patterns between SRL interventions and measurements, except for Araka et al.’s (2020) review. Although Araka et al. (2020) conducted a review similar to ours, their focus was limited to e-learning environments. This restriction aligns with their goal of modeling educational data mining for supporting SRL, rather than embedding SRL support into existing learning activities that may or may not involve technology or have sufficient data for data mining. Despite this, they provided valuable insights into relevant themes and challenges. Our study distinguishes itself from similar research through its broader scope, encompassing both technology-assisted SRL interventions and those without technology. While our primary goal is to integrate technology into SRL support, understanding traditional methods remains crucial for defining the role of technology in our future model.

**Table 1. Examples of relevant previous literature reviews**

<b>Review title</b>	<b>Insights given</b>	<b>Limitation or scope</b>
<i>Tools to support self-regulated learning in online environments: Literature review</i> (Pérez-Álvarez et al., 2018)	List of SRL support tools Features What strategies are supported by each tool Impact on students’ SRL abilities	Limited to online environments like MOOCs Only discuss the interventions with tools

Review title	Insights given	Limitation or scope
<i>Supporting self-regulated learning in online learning environments and MOOCs: A systematic review</i> (Wong et al., 2019)	Intervention theme or category Research objective theme from each intervention category Impact on student SRL abilities Impact on student academic performance Impact of human factors	Limited to online learning environments Only discussed the interventions, not discussing the measurements and the association between interventions and measurements
<i>Research trends in measurement and intervention tools for self-regulated learning for e-learning environments – systematic review (2008-2018)</i> (Araka et al., 2020)	List and categories, as well as trends in SRL interventions List and categories, as well as trends in SRL measurements Use of educational data mining to measure and improve SRL	Limited to e-learning environments
<i>Using the personal learning environment to support self-regulated learning strategies: A systematic literature review</i> (Nan Cenka et al., 2022)	PLE research themes to support SRL List of theories that explain why PLE is suitable for SRL The role of PLE in supporting SRL List of PLE platforms to support SRL	Limited to personal learning environment Only focused on one type of SRL intervention
<i>Supporting self-regulated learning with learning analytics interventions – a systematic literature review</i> (Heikkinen et al., 2023)	List and category of learning analytics methods List of learning analytics platforms Mapping of SRL phases targeted by learning analytics List of intervention evaluation methods	Limited to learning analytics interventions Only discussed the interventions, not discussing the measurements and the association between interventions and measurements
<i>Self-regulated learning in the digital age: A systematic review of strategies, technologies, benefits, and challenges</i> (Faza & Lestari, 2025)	List of technologies that support SRL List of SRL benefits List of SRL challenges	Limited to technology-based intervention Only discussed the interventions, not discussing the measurements and the association between interventions and measurements
This review	List of categories and trends of SRL interventions List of categories and trends of SRL measurements Association of SRL interventions and measurements The discussion was directed towards a holistic, integrated, and technology-assisted model	Response to the gap Gather insights from both conventional and technology-assisted interventions to bridge existing learning design into the holistic, integrated, and technology-assisted model.

## METHODOLOGY

In this review, we followed the Guidelines for Performing Systematic Literature Reviews in Software Engineering, formulated by Kitchenham and Charters (2007), which share conceptual similarities with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et

al., 2021), but differ slightly in terminology. For example, Kitchenham and Charters’ (2007) guidelines use the term “inclusion criteria” for article selection, but are referred to as “eligibility criteria” in PRISMA. While PRISMA provides a checklist for critically appraising primary studies, Kitchenham and Charters’ (2007) guidelines prioritize the reliability of insights derived from the articles (Kitchenham et al., 2023). Despite these similarities, the guidelines diverge in focus: PRISMA’s origins in medical studies emphasize quantitative precision, whereas the multidisciplinary nature and limited empirical research in software engineering studies necessitate greater flexibility. Therefore, we selected the Kitchenham and Charters’ (2007) guidelines as our primary framework while acknowledging PRISMA’s broader recognition. This review maintains rigor and transparency by adhering to the Software Engineering Guidelines for Reporting Secondary Studies (SEGRESS) and drawing inspiration from the PRISMA 2020 checklist for reporting systematic literature reviews in the software engineering context (Kitchenham et al., 2023).

Following the systematic review methodology outlined by Kitchenham and Charters (2007), the research progressed through planning, literature search and selection, and data extraction. The planning stage involved defining criteria for article databases, selecting relevant keywords, defining criteria for article inclusion, assessing quality, and extracting data. During data extraction, we recorded the selected articles’ publication year, country, HE context, and data collection techniques, as well as any SRL interventions. Qualitative content analysis was then conducted for both the data collection techniques and the SRL interventions to discern trends over time, as these trends are foundational to developing an integrated and holistic conceptual model for SRL implementation and measurement. The research stages of this study are visualized in Figure 1.

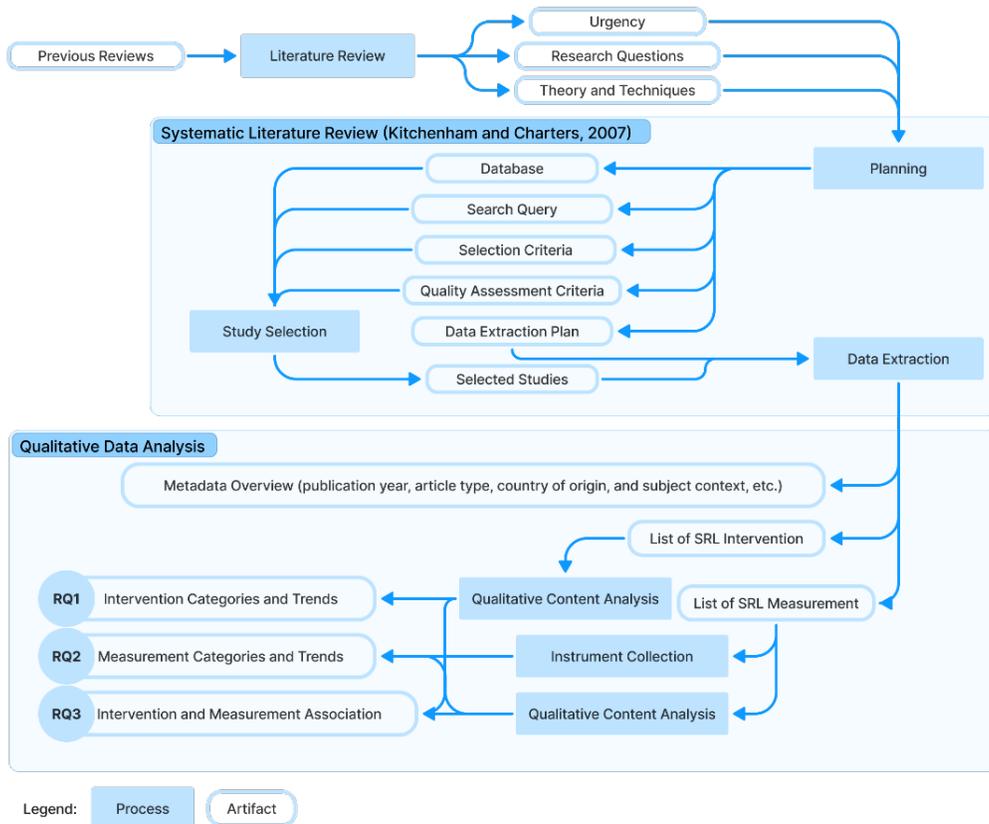


Figure 1. The research methodology of our study

All steps in this review are conducted by one of the authors and periodically monitored by all authors, rather than being automated by tools. However, some tools were used during the process to make manual work easier. These tools include Zotero for managing article metadata and overseeing each step of article selection, and Google Spreadsheets for managing extracted data as structured tables, analyzing, creating pivot tables, and generating charts for reporting.

### ***LITERATURE SEARCH AND SELECTION PROTOCOL***

The literature search was focused on HE contexts involving SRL interventions without limiting such interventions to technological interventions so that we could capture diverse approaches. Nine databases were searched, namely Scopus, ScienceDirect, IEEE Xplore, ACM Digital Library, ERIC, Taylor and Francis Online, Emerald Insight, SpringerLink, and Sage Journals. We employed keywords tailored to the population, intervention, and comparison criteria, along with Boolean operators and wildcards for added flexibility. The search query used for searching through the databases was ('self-regula\*' OR 'co-regula\*' OR 'self regula\*' OR 'co regula\*') AND ('higher education' OR 'university' OR 'college' OR 'undergraduate') AND ('intervention' OR 'treatment' OR 'foster\*' OR 'experiment\*'), making minor adjustments for the capability of each database.

The process of selecting literature involved evaluating metadata, titles, abstracts, and full-text relevance to identify the most suitable content. Several criteria were considered during this process. From the metadata, we ensured that the articles are either journal articles or conference papers, confirming they have undergone peer review before publication. We also limit our inclusion to articles published before 2013 to ensure relevance over time, while capturing technological changes, including research related to pre- and post-COVID-19 contexts. SRL-relevant keywords should appear in the title, abstract, and full text to ensure the article discusses SRL intervention in the HE context. We make every effort to access the full text via the author's institutional subscription. For articles that we cannot access through our subscription, we search for alternative platforms such as ResearchGate.

Additionally, we set criteria to ensure the quality of the reviewed articles, as they must provide the necessary insights to answer our research questions. Specifically, the articles should be indexed in Scopus and written in English to ensure quality for an international audience. They should also clearly explain the SRL intervention being implemented and include some form of SRL measurement that aligns with both the HE context and the SRL intervention studied. The subsequent quality assessment prioritized substantive content over publication reputation, focusing on relevance to the research questions and extraction plan. All criteria were agreed upon by consensus among all authors. The literature selection process was conducted by one author, with periodic reviews and approval by all authors. The entire process, including detailed exclusion criteria and article numbers across the various selection phases, is presented in Figure 2, following the PRISMA 2020 flowchart style.

The distribution of the selected articles based on article type, geographical affiliation, and publication year is shown in Figure 3. Most of the selected literature consisted of journal articles ( $n = 95$ ), with only 14 being conference articles or proceedings. While we aimed to include literature from 2013 to 2023 for our review, the selected publications ranged from 2014 to 2023. The distribution of publications displays an increasing trend over the years, with minor fluctuations in 2017, 2021, and 2022. The literature originated from 24 countries, including Germany, the United States, China, Turkey, Japan, Spain, Iran, and others. Germany contributed the most publications ( $n = 16$ ), followed closely by the United States ( $n = 15$ ), China ( $n = 12$ ), and Taiwan ( $n = 10$ ). Subject areas varied, with computer science and information systems ( $n = 17$ ), foreign language learning ( $n = 14$ ), and teacher education ( $n = 12$ ) being the most common. Notably, 26 studies did not specify the study subject in relation to the population studied.

We further perform data extraction on SRL interventions and measurements to answer all of our research questions. Then, we conduct a qualitative content analysis (QCA) to identify common themes in SRL interventions and measurements. Next, we analyze the trends and the associations between categories.

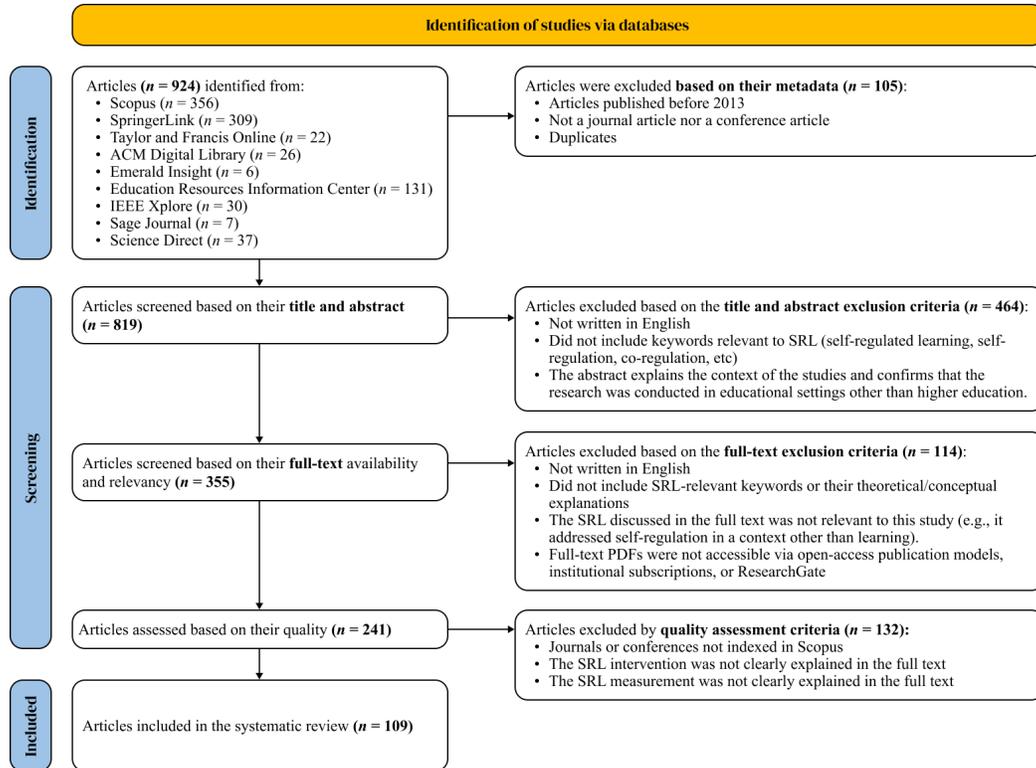


Figure 2. PRISMA 2020 flowchart of article selection done in this review

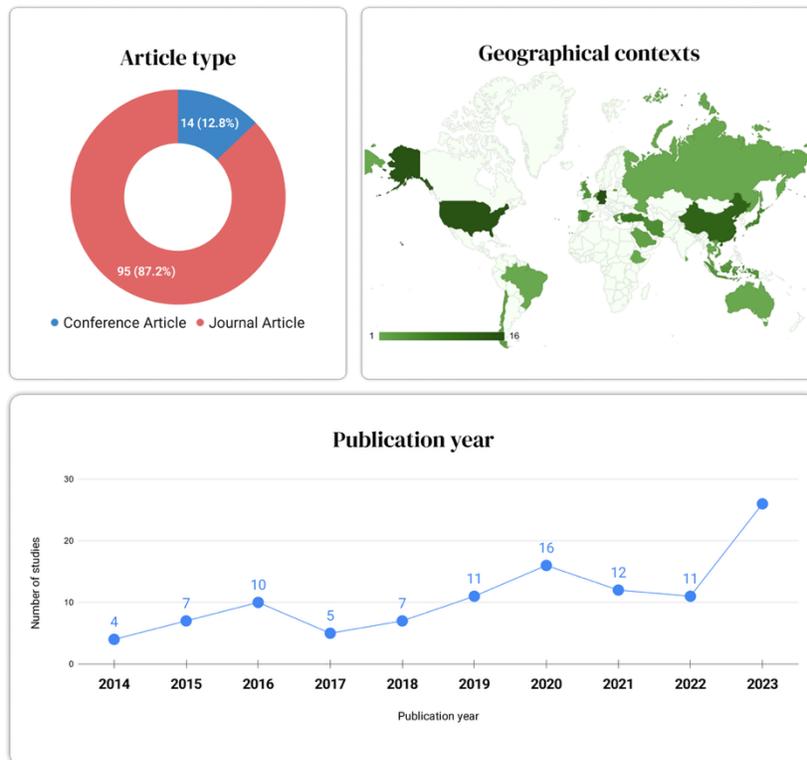


Figure 3. Reviewed articles overview by type, geographical contexts, educational subject, and publication year

## ***QUALITATIVE DATA ANALYSIS, PROVISIONAL CODING, AND CODING FRAME***

The extracted data underwent qualitative analysis using the QCA method, guided by Schreier's (2012) guidelines, which systematically interpret qualitative data through classifications based on a coding frame. Adopting Saldaña's (2013) provisional coding technique, predefined codes were used, allowing for the emergence of new codes or adjustments to initial ones, with reference to prior research for developing the coding framework. Both the categorization of SRL interventions and measurements were conducted by one of the authors and were periodically reviewed by all authors, who approved the final version.

To address RQ1, we employ QCA provisional coding, drawing on insights from prior research to establish a coding frame. Araka et al. (2020) categorized interventions into feedback-based, instruction-based, prompt-based, and software-based interventions, while Pérez-Álvarez et al. (2018) identified planning and evaluation as widely supported SRL aspects according to the software used. Additionally, Theobald (2021) specifically studied the impact of SRL training on academic performance. Hence, we formulated a coding framework that included planning-based, feedback- or report-based, training-based, prompt-based, and technology-assisted interventions. While conducting the QCA provisional coding, we identified two new codes: assessment-based and reflection-based interventions. The whole coding frame, along with a description of each code, is displayed in Table 2. Later in the Results section, we will display the examples of each category. It is noteworthy that each article could have multiple codes.

**Table 2. Coding frame of SRL interventions**

<b>Category</b>	<b>Description</b>	<b>Source of category</b>
Planning	Interventions that involve or support the planning aspect within the SRL process.	Pérez-Álvarez et al. (2018)
Feedback/report	Interventions that involve or support the monitoring aspect within the SRL process, in the form of reporting student strategy data or providing feedback.	Araka et al. (2020)
Training	Interventions that involve training or special classes that teach learning strategies and SRL concepts.	Theobald (2021)
Assessment	interventions that involve an assessment process, which then serves as a reference for students to improve their SRL abilities.	New code emergence. Will be discussed in the Results section.
Prompt	Interventions in the form of instructions to trigger or direct students to carry out SRL activities.	Araka et al. (2020)
Reflection	Interventions that involve or support the reflection aspect within the SRL process.	New code emergence. Will be discussed in the Results section.
Technology-assisted	Interventions that involve the use of technology to assist it.	Araka et al. (2020)

To answer RQ2, we also coded SRL measurements using QCA, starting with the SRL measurements listed in Winne and Perry's (2000) SRL measurement guideline. We then refined these categories to better align with our data. We noticed many articles used self-reported data through scales and open-ended questions. Because of this, we split the original category, "Self-Report Questionnaires," into "Quantitative Questionnaires" and "Qualitative Questionnaires." We changed "Think Aloud Measures" to the more common "Think Aloud Protocol." We also renamed "Trace Methodologies"

to “Information System Data” to better reflect the user events or system logs from learning environments, such as LMS or MOOCs. However, we did not find “Teacher Judgement,” “Error Detection Tasks,” or “Observation of Performance” as defined by Winne and Perry (2000). Instead, we found focus group discussions and assessment data. While assessment data could be seen as “Observation of Performance,” we believe they are different. Winne and Perry (2000) emphasize behavior in “Observation of Performance,” but the assessment data in our articles focused on final scores. In total, we used seven codes for our coding, as shown in Table 3, with two codes created during the coding process.

**Table 3. Coding frame of SRL measurements**

Category	Description	Source of category
Quantitative questionnaire	Self-reported data in the form of scale-based questionnaire responses.	Defined by Winne and Perry (2000) originally as “Self-Report Questionnaires”. Also identified in Araka et al.’s (2020) review.
Qualitative questionnaire	Self-reported data in the form of open-ended questionnaire responses.	Defined by Winne and Perry (2000) originally as “Self-Report Questionnaires”.
Interview	Data collection method that involves direct, in-depth conversations with individuals about a particular topic or set of issues.	Defined by Winne and Perry (2000) originally as “Structured Interview”.
Focus group discussion	A data collection method that involves gathering people from similar backgrounds or experiences to discuss a specific topic.	New code emergence. Will be discussed in the Results section.
Think-aloud protocol	Data collection method where participants share their thoughts verbally while performing tasks.	Defined by Winne and Perry (2000) originally as “Think Aloud Measures”.
Information System Data	Logs, or trace data, are found or collected within the learning system.	Defined by Winne and Perry (2000) originally as “Trace Methodologies”. Also identified in Araka et al.’s (2020) review.
Assessment Data	Assessment scores that depict students’ performance.	New code emergence. Will be discussed in the Results section.

Additionally, we also extracted quantitative questionnaires from articles that use a quantitative questionnaire as their data collection method. We also extracted the constructs or SRL dimensions that were measured by those questionnaires. We conduct QCA provisional coding based on Butler and Cartier’s (2005) SRL-in-Context model.

### ***CODE ASSOCIATION ANALYSIS***

To answer RQ3 and as part of the association exploration while addressing RQ1 and RQ2, we examined the relationships between code frames using the Jaccard Index coefficient, which measures the similarity between two sets by calculating the ratio of the intersection size to the union size (Leskovec et al., 2014). For example, the Jaccard Index for a set of documents indexed as code  $A$  and a set of documents indexed as code  $B$  is expressed as follows:

$$J(A, B) = \frac{N_{A \cap B}}{N_A + N_B - N_{A \cap B}}$$

With details as follows:

- Let  $N_A$  be the frequency of code  $A$ .
- Let  $N_B$  be the frequency of code  $B$ .
- Let  $N_{A \cap B}$  be the frequency of co-occurrence of codes  $A$  and  $B$ .

Our QCA process generated quantized data showing how often each code appeared. The Jaccard Index measures the similarity between two binary codes, taking into account their frequency (Leskovec et al., 2014). This allows us to consider all code occurrences, not just the frequent ones. We use the Jaccard Index to determine how often codes co-occur; this is not to make quantitative claims or test a hypothesis. Analyzing code co-occurrence based solely on frequency can be misleading because a frequently occurring code may appear with many others simply because it is common. The Jaccard Index addresses this by factoring in the individual frequency of each code (Leskovec et al., 2014). Qualitative data analysis, such as NVivo, also utilizes this approach to cluster documents based on both word and code similarity (Lumivero Community, 2023). We use Google Sheets to conduct the QCA, and all analysis is performed in Google Sheets, Observable Notebook, and Jupyter Notebook environments.

## RESULTS

### *ADDRESSING RQ1: TRENDS OF SELF-REGULATED LEARNING INTERVENTIONS*

The SRL interventions extracted from the selected literature were categorized. These categories included planning-based, feedback- or report-based, training-based, reflection-based, assessment-based, prompt-based, and technology-assisted interventions. The number of articles in each category, along with examples of each, is presented in Table 4.

**Table 4. Intervention list per category, N is the number of articles**

Intervention category	$N$	Example of a conventional intervention	$N$	Example of a technology-assisted intervention	$N$
Planning-based interventions	20	Provision of an assessment rubric for each instruction (Fraile et al., 2023; Y. Xu, 2020)	8	Planning apps like 4Planning (Jaramillo et al., 2022; Lobos et al., 2021) and the Hierarchical Goal Planning System (Weber et al., 2021)	12
Feedback- or report-based interventions	40	Conventional feedback (Chida & Minamino, 2023; Nakata, 2020) Peer feedback (Udvardi-Lakos et al., 2023)	11	Learning analytics dashboards (Cavus Ezin & Yilmaz, 2023; Li et al., 2022; Lim et al., 2021; Nelissen, 2023; Piotrkowicz et al., 2017; Ustun et al., 2023) An intelligent tutoring system or pedagogical agent (Azevedo et al., 2016; Cerezo et al., 2020; Martha et al., 2023; Taub et al., 2014; Trevors et al., 2014)	29
Training-based interventions	24	Conventional training (Dörrenbächer & Perels, 2016; Nejabati, 2015)	21	Web-based training (Bellhäuser et al., 2016)	3
Reflection-based interventions	32	A journal or learning diary (Zarei Hajiabadi et al., 2022)	22	An e-portfolio (Alexiou & Paraskeva, 2020; Nguyen & Ikeda, 2015)	10

Intervention category	N	Example of a conventional intervention	N	Example of a technology-assisted intervention	N
Assessment-based interventions	31	A formative assessment (Weldmeskel & Michael, 2016)	20	Interactive videos and embedded quizzes (Silverajah & Govindaraj, 2018)	11
Prompt-based interventions	19	Reminder or trigger instructions for conducting SRL strategies in a conventional classroom context (Heller & Marchant, 2015; Yabukoshi, 2023)	14	Division of the instructions in the LMS into three SRL phases (Paraskeva et al., 2017)	5

When examining year-to-year trends, as shown in Figure 4, nearly all intervention categories have remained relatively stable. In 2023, with the highest total number of articles reviewed that year, several categories saw an increase. Notably, there was a significant rise in the categories of feedback/report-based, assessment, and technology-assisted interventions. When separating conventional from technology-assisted interventions, a sharp increase was observed in conventional interventions across both assessment-based and feedback/report categories. Conversely, in technology-assisted interventions, only the increase in feedback/report interventions was more pronounced than in other categories.

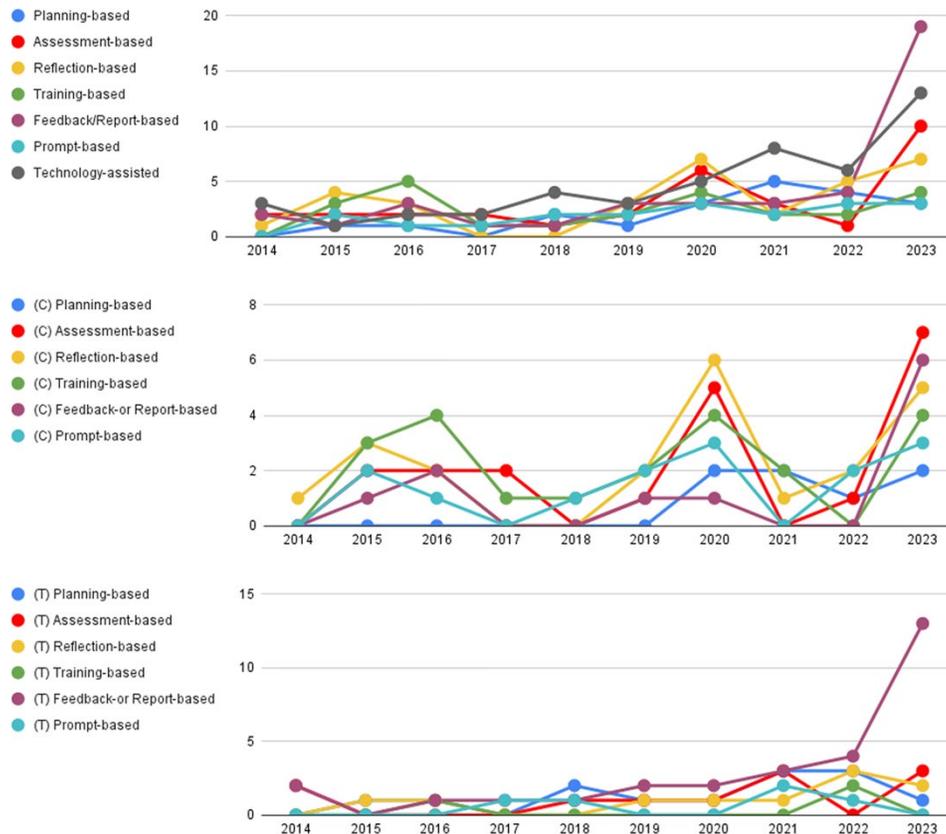


Figure 4. Trends in SRL intervention categories over the years, including both conventional and technology-assisted (top), only conventional (middle), and only technology-assisted (bottom)

Many articles featured several combinations. Figure 5 shows the number of articles for each category combination in descending order of combination degree. A total of seven studies included a combination of assessment-based, feedback- or report-based, and technology-assisted interventions. For example, Han et al. (2021) and Hou (2020) utilized an automatic evaluation system to provide indirect feedback from assessments using technology. Furthermore, three studies were categorized into five different categories. For example, the 4Planning application features related to planning and reflection, providing feedback and prompts to students to complete the stages of SRL (Jaramillo et al., 2022; Lobos et al., 2021). Most combinations with a relatively large degree of combinations involve technology to support them.

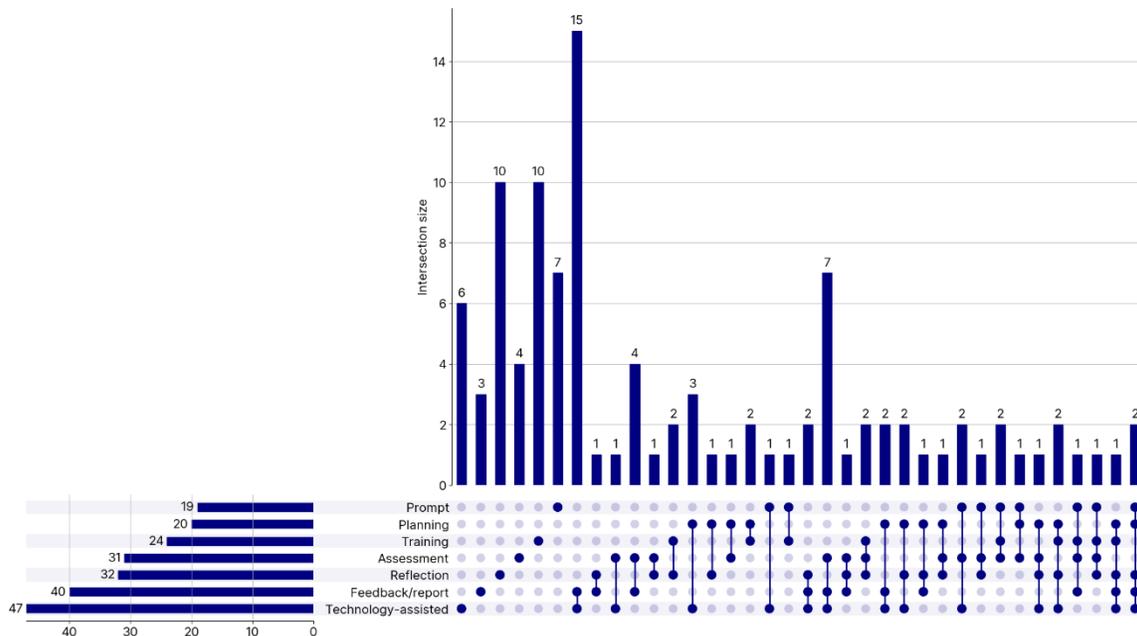


Figure 5. Distribution of the number of articles for each category combination

Focusing on the association among all pairs reveals that several category pairs show a notable connection compared to others, as shown in Figure 6. The strongest association, indicated by a 0.5 Jaccard Index, is between feedback/report-based interventions and technology-assisted interventions. Many articles in these two categories are studies aimed at supporting SRL with LADs. Five articles used a LAD to encourage students to monitor their learning (Cavus Ezin & Yilmaz, 2023; Li et al., 2022; Lim et al., 2021; Nelissen, 2023; Piotrkowicz et al., 2017; Ustun et al., 2023). A LAD that targets students directly is referred to as a student-facing LAD. Besides LADs, reports or feedback can also be provided through an intelligent tutoring system or pedagogical agent (Azevedo et al., 2016; Cerezo et al., 2020; Martha et al., 2023; Taub et al., 2014; Trevors et al., 2014). This finding aligns with Araka et al.’s (2020) review, which states that LADs, software agents, and feedback are interventions that can enhance SRL abilities in e-learning environments. Another noteworthy association, although with a slightly lower Jaccard Index, is the link between planning-based and reflection-based interventions.

In summary, to address RQ1, “What trends are present in SRL interventions, both technology-assisted and non-technology-assisted, within the context of higher education?” some trends in SRL have been identified. First, previous studies support SRL through various methods, including both technological and traditional approaches. The trend toward technology-assisted interventions is growing, especially in feedback- and planning-based approaches, while training, assessment, reflection, and prompt-based methods remain mostly conventional. Most studies focus on one or two types of interventions, but a few combine different approaches into a single method, usually with

technological support. The most notable connection is between feedback- and report-based interventions and technology assistance. This link highlights the growing use of technology and its data to deliver data-driven insights for students. These insights will be explored further in the RQ3 results. The implications and recommendations are provided in the Discussion section.

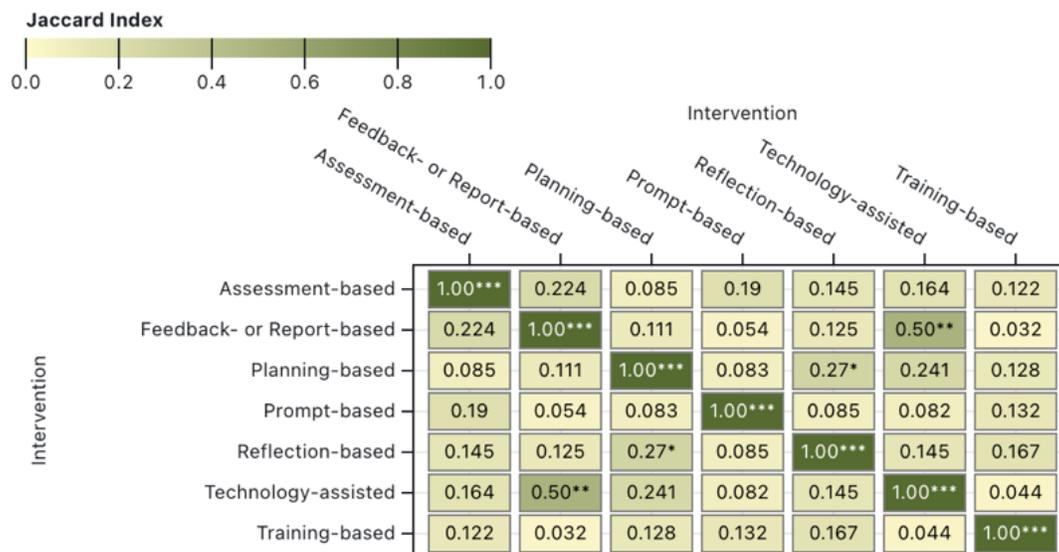


Figure 6. All intervention pairs Jaccard Index contingency matrix, with associations indicated as follows: higher Jaccard Index marked with \*\*\*, between 0.5 and 0.75 marked with \*\*, and between 0.25 and 0.5 marked with \*

### ADDRESSING RQ2: TRENDS OF SELF-REGULATED LEARNING MEASUREMENT

Our study included 79 studies that collected data via questionnaires, 47 studies that collected data via assessments, 12 studies that conducted interviews, seven studies that collected qualitative data via questionnaires containing open-ended questions, 19 studies that utilized system data, and four studies that collected data via think-aloud protocols (Figure 7). Most articles combined several data collection techniques simultaneously to enrich their findings about SRL. Specifically, 33 articles used questionnaires only, while 20 articles combined questionnaires with assessments or student scores on specific exams or tests.

When analyzing trends over the years, as shown in Figure 8, data collection primarily relied on quantitative questionnaires, followed by assessments and data from information systems. Although both the think-aloud protocol and information system logs are considered event-based measurements by Winne and Perry (2000), we observe different trends from each. The number of studies using system data steadily increased, especially after 2020, while studies employing the think-aloud protocol were only published up to 2018. A similar pattern was observed in a literature review by Silverajah et al. (2022), which included a small number of studies that employed the think-aloud protocol; however, many studies relied on questionnaires. Roth et al. (2016) noted that the think-aloud protocol offers valuable insights into the learning process. However, the complexity of instructions during this protocol can make it difficult for participants to verbalize their actions, resulting in a reduction in the quality of data.

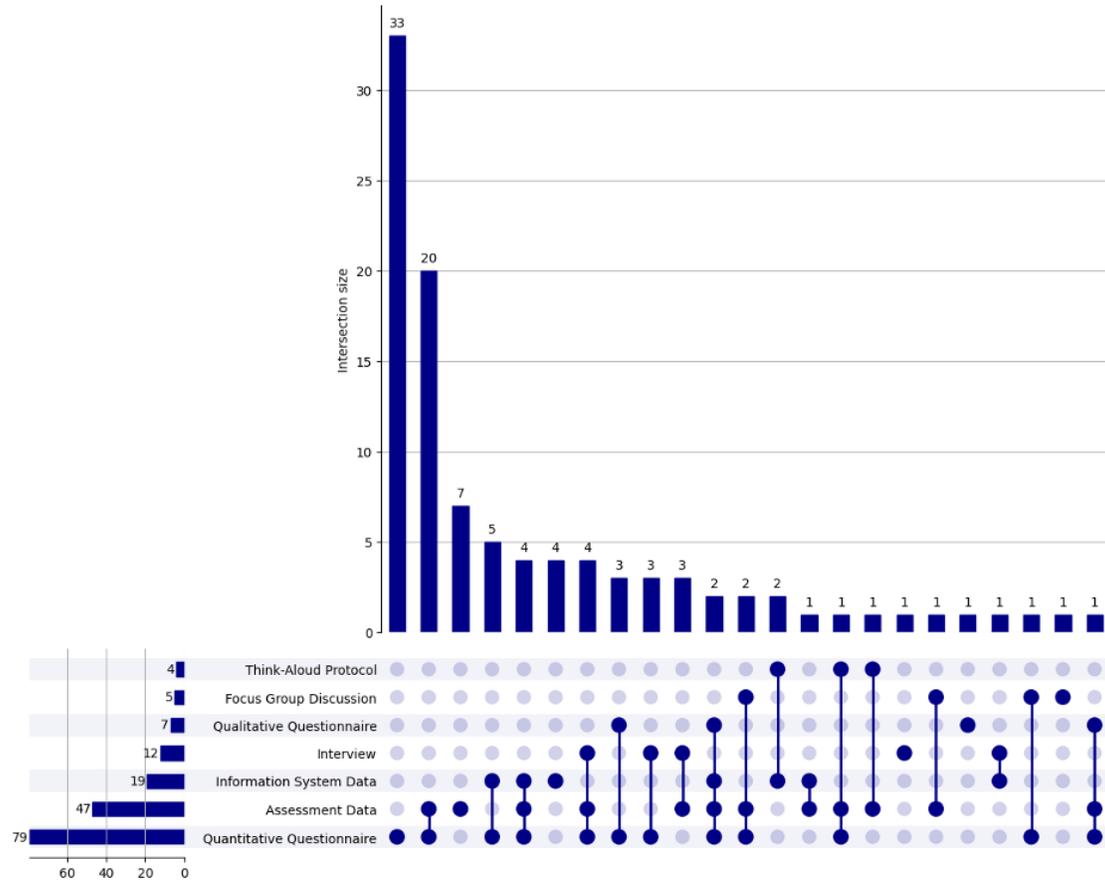


Figure 7. Distribution of the number of articles for each combination of data collection techniques

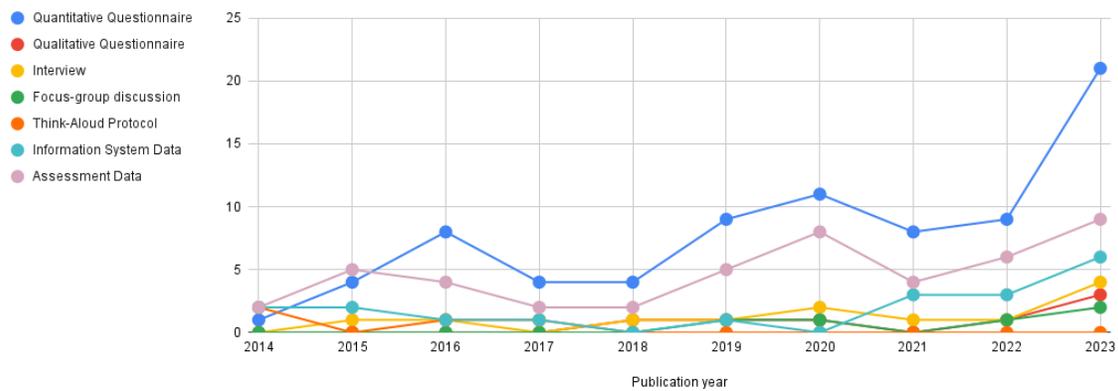
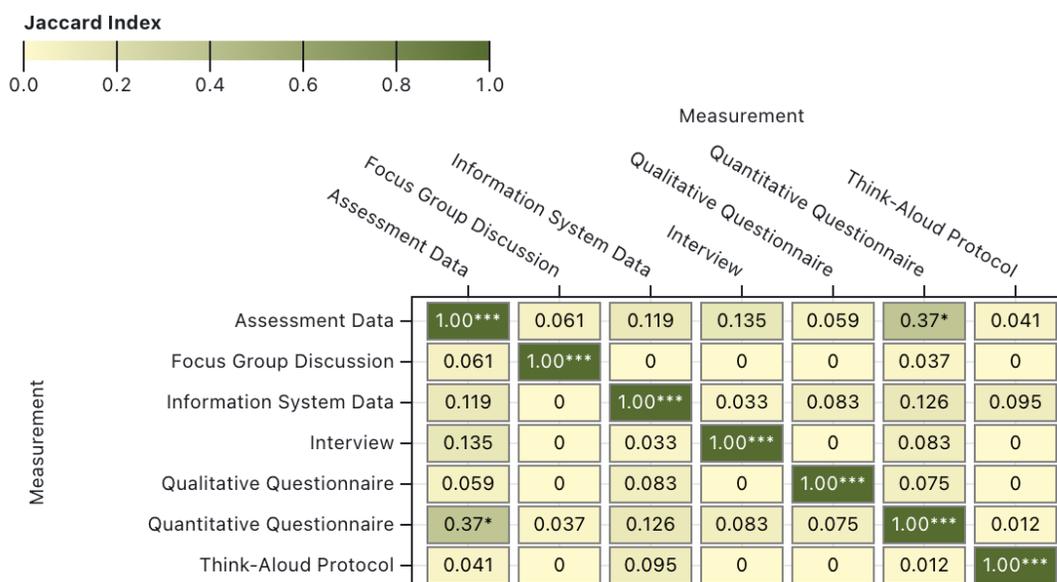


Figure 8. Trends in data collection techniques

When it comes to the pair combination association depicted in Figure 9, the pairing of quantitative questionnaires and assessment data is notable. These studies, which combined questionnaires with student score data, generally aimed to discover the relationship between SRL abilities and student performance (Altas & Mede, 2021; Chen & Su, 2019; Follmer et al., 2022; Midun et al., 2019). However, some studies also compared SRL abilities among students with high performance (characterized by high academic grades) and students with low performance (characterized by low academic grades), as was done in Kuo et al.'s (2023) study.



**Figure 9.** All measurement pairs are presented in a Jaccard Index contingency matrix, with associations indicated as follows: higher Jaccard Index values are marked with \*\*\*, those between 0.5 and 0.75 are marked with \*\*, and those between 0.25 and 0.5 are marked with \*

Many previous studies have used quantitative questionnaires that focus on measuring various constructs. As shown in Table 5, our review included 28 different questionnaires, with the Motivated Strategies for Learning Questionnaire being the most widely used. Other popular tools included the Online SRL Questionnaire, Writing Strategies for SRL Questionnaire, Metacognitive Awareness Inventory, and Learning and Study Strategies Inventory.

**Table 5. Questionnaires that were used in the reviewed articles**

Questionnaire name	<i>N</i>
Motivated Strategies for Learning Questionnaire (Pintrich & De Groot, 1990)	22
Online SRL Questionnaire (Barnard et al., 2009)	9
Writing Strategies for SRL Questionnaire (Teng & Zhang, 2016)	5
Metacognitive Awareness Inventory (Schraw & Dennison, 1994)	4
Learning and Study Strategies Inventory (Weinstein et al., 1988)	2
Learning Strategies for Students (Theobald & Bellhäuser, 2022)	2
Procrastination Questionnaire for Students (Theobald & Bellhäuser, 2022)	2
Professional Self-Efficacy (Theobald & Bellhäuser, 2022)	2
Specially formulated SRL questionnaire (Dörrenbächer & Perels, 2016)	2
Academic SRL Scale for Writing (Magno, 2009)	1
Cross-Curricular Competencies Strategy Scale (Samuelstuen & Bråten, 2007)	1
Questionnaire to Assess Learning Strategies in University Students (Gargallo et al., 2014)	1
General Regulatory Focus Measure (Lockwood et al., 2002)	1
Metacognitive Construct for Communities of Inquiry (Garrison & Akyol, 2013)	1
Reflective Thinking Questionnaire (Kember et al., 2000)	1

Questionnaire name	<i>N</i>
Strategy Inventory for Language Learning (Oxford, 1990)	1
SRL Questionnaire for University Students (Bellhäuser et al., 2016)	1
SRL Opportunities Questionnaire (Vrieling et al., 2013)	1
Self-Regulatory Traits Model (Hong & O'Neil, 2001)	1
Scale on Self-Regulation in Learning (Erdogan & Senemoglu, 2016)	1
Task-Specific Strategy Scales (Samuelstuen & Bråten, 2007)	1
Achievement Goal Framework (Elliot et al., 1999)	1
Specially formulated SRL questionnaire (Suraworachet et al., 2023)	1
Volitional Components Questionnaire (Forstmeier & Ruddel, 2008)	1

*N*: Number of reviewed studies that used the instrument

While most questionnaires assessed general SRL abilities across emotional, cognitive, and metacognitive aspects, some were tailored to specific subject areas. For instance, the Writing Strategies for SRL Questionnaire and Strategy Inventory for Language Learning were used to analyze SRL strategies within writing and language learning contexts. Some questionnaires incorporated other theories, such as the community of inquiry theory, as seen in Garrison and Akyol's (2013) questionnaire.

Some constructs were measured using more than one questionnaire, as each questionnaire differs in its definitions of the constructs under study or in how these constructs are mapped to different indicators. In this study, these constructs were coded as the SRL dimensions of Butler and Cartier (2005). This mapping of constructs to SRL dimensions is presented in Table 6.

**Table 6. Constructs from the questionnaire used in the reviewed article**

SRL dimension	Construct	<i>N</i>
Context utilization	Environmental control	4
	Help-seeking	6
	Social strategy	1
	Collaboration	5
Student characteristics	Concentration	5
	Decision making	1
	Procrastination	2
	Responsibility	1
	Time management	7
	Volitional control	2
Mediator: Knowledge	Declarative knowledge	1
	Conditional knowledge	1
	Procedural knowledge	1
Mediator: Emotion	Affective strategy	1
	Anxiety	4
	Emotional control	2
	Impulse control	1
Mediator: Metacognition	Epistemological beliefs	1
	Knowledge of cognition	1
	Metacognitive awareness	1
	Metacognitive strategy	2

<b>SRL dimension</b>	<b>Construct</b>	<b>N</b>
Mediator: Motivation	Attitude	1
	Effort	3
	Interest enhancement	1
	Intrinsic motivation	2
	Extrinsic motivation	1
	Motivational control	1
	Persistence	3
Mediator: Perception	Attribution	4
	Habitual actions	1
	Initiative	1
	Preventive regulatory focus	1
	Promotive regulatory focus	1
	Self-efficacy	6
Task interpretation	Task interpretation	2
	Task perception	1
	Task value	4
Cognitive strategy	Compensation strategy	1
	Elaboration	2
	Information processing strategy	4
	Information seeking strategy	5
	Information selection strategy	1
	Knowledge application	1
	Memorization	8
	Information organization strategy	6
	Personalization and creativity	1
	Task-specific strategy	3
SRL strategy: Planning	Goal setting	7
	Strategic Planning	8
SRL strategy: Monitoring	Monitoring	13
SRL strategy: Evaluation	Critical thinking	1
	Evaluation	8
	Self-assessment	3
	Reflection	3
SRL strategy: Adjustment	Consequence coping	3
	Feedback coping	1

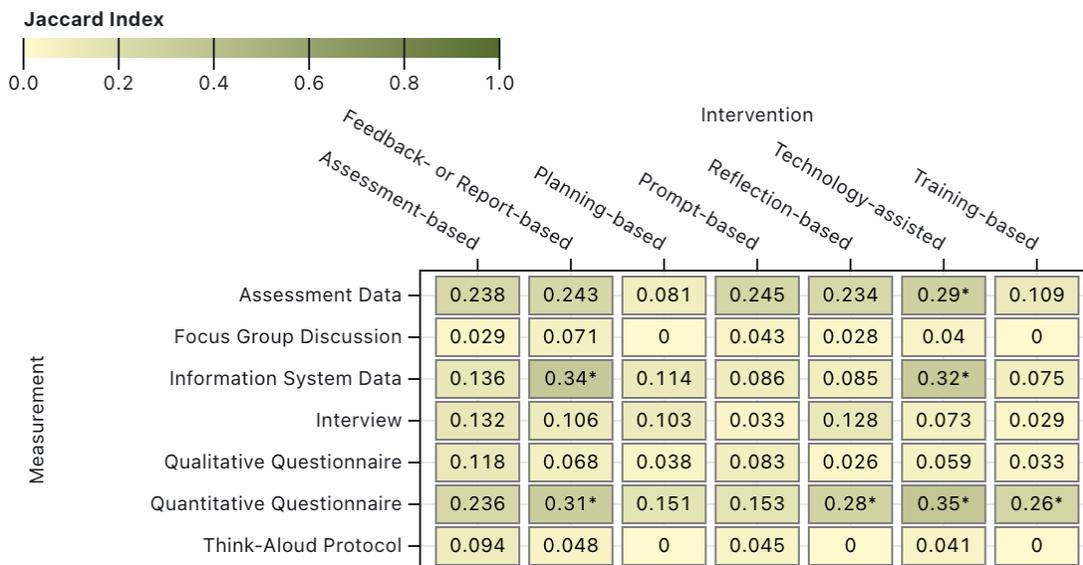
N: Number of instruments that measure the construct in the reviewed studies

According to the construct mapping, our findings suggest that previous studies have collectively measured all aspects of SRL, at least within the SRL-in-Context model (Butler & Cartier, 2005). This suggests that quantitative questionnaires offer a clear pathway to understanding SRL, providing numerous options for combining instruments to assess various facets, from context and personal traits to specific SRL strategies. However, it is important to note that quantitative, scale-based questionnaires rely on self-reporting, making them dependent on students' beliefs and perceptions of their own conditions (Winne & Perry, 2000). In the discussion, we explore the combination of different measurement types, specifically SRL measurements as an aptitude and SRL measurements as an event (Winne & Perry, 2000)

In summary, to address RQ2, “What trends are present in the measurement of SRL within the context of higher education?” we found that the primary trend in measuring SRL involves the use of quantitative questionnaires, followed by assessment data, with both often combined. This highlights the trend of measuring SRL from an academic performance perspective. Additionally, we observed differences in trends between event-based measurements. The think-aloud protocol is rarely used; however, information system logs are employed more frequently, and this trend is growing, indicating a shift toward more digital solutions for capturing SRL events. We also note the use of self-reported questionnaires. When all the questionnaires used in previous research are combined, all aspects of SRL have been collectively measured. Future research could combine multiple questionnaires to capture all dimensions of SRL fully. In the Discussion section, we highlight the strengths and weaknesses of aptitude-based questionnaires and offer recommendations on how to also strive for comprehensive dimension coverage in event-based SRL measurement.

**ADDRESSING RQ3: ASSOCIATION BETWEEN SRL INTERVENTION AND MEASUREMENT**

To analyze the relationship between interventions and measurements, the Jaccard Index was calculated and presented as a contingency matrix in Figure 10. There were no strong associations between the pairs. However, some associations were noticeable, although the Jaccard Index values were low (ranging from 0.25 to 0.5). For instance, four out of seven intervention categories showed a small yet noticeable association with quantitative questionnaire and assessment data measurements, possibly because both are commonly used across various intervention types. For qualitative data, including questionnaires, interviews, focus group discussions, and think-aloud protocols, the Jaccard Index values are even lower (below 0.25). This might be because qualitative data is often used to explain findings from primary quantitative data.



**Figure 10. All intervention and measurement pairs Jaccard Index contingency matrix, with associations indicated as follows: higher Jaccard Index marked with \*\*\*, between 0.5 and 0.75 marked with \*\*, and between 0.25 and 0.5 marked with \***

The top three most associated pairs are between quantitative questionnaires and technology-assisted interventions, between information system data and feedback/report-based interventions, and between information system data and technology-assisted interventions. As mentioned in the explana-

tion of intervention trends, feedback/report-based interventions and technology-assisted interventions had a moderate association. Mainly, technology-assisted interventions combined with feedback or report-based interventions incorporated LADs and system data like LMSs and MOOCs to assess and illustrate student learning behaviors and SRL abilities. These findings align with the trends highlighted by Araka et al. (2020), which show that the use of learning analytics and educational data mining is a significant trend in the development of SRL measurement.

In summary, to answer RQ3, “How do the identified trends in SRL interventions and measurements relate to one another in prior studies?” we examine the Jaccard Index for every pair of interventions and measurements. We did not find any moderate to strong associations. This indicates that no clear pattern was identified from previous studies. However, from the small associations that were found, we can draw some insights, including that most studies likely use quantitative questionnaires and assessment data, regardless of the type of intervention they conduct. We also highlight pairs with the highest association scores, such as between technology-assisted interventions, information system data, and feedback/report-based interventions. As mentioned earlier, the use of information system logs is categorized as event-based SRL measurement according to Winne and Perry (2000). This association shows that many studies utilize technology and its logs to provide students with data-driven insights into how they learn, especially from the perspective of SRL events.

## DISCUSSION

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Regarding RQ1, our findings confirm and expand previous reviews by providing a more detailed overview of SRL interventions. While earlier reviews, such as those by Araka et al. (2020), Pérez-Álvarez et al. (2018), and Wong et al. (2019), primarily focused on online and e-learning contexts, our broader scope enables us to identify a wider range of SRL interventions and their applications. Building on Araka et al.’s (2020) foundational research, which examined feedback-based, prompt-based, and technology-assisted strategies, our analysis highlights interventions outside online settings that are less often documented. Specifically, we emphasize the importance of training, reflection, planning, and assessment-focused strategies. Additionally, our study enhances the understanding of technology’s role, revealing a consistent pattern: feedback-based interventions are predominantly supported by technology. We identify key tools involved, such as LADs, intelligent tutoring systems, and pedagogical agents. By doing so, we not only confirm established trends but also highlight the specific technology tools that enable these strategies, offering valuable updates to the existing literature. Unlike prior research that may focus only on technological solutions, our approach stresses that technology should serve the needs of traditional educational environments (Kalyani, 2024; Zou et al., 2025). This view helps bridge the gap between digital and conventional learning, providing practical solutions that are not just “technology for technology’s sake,” but aim to address real-world educational challenges.

Regarding RQ2, our findings align with Araka et al.’s (2020) review, which identified self-reported data as the most established method for measuring SRL. Building on this, we found that combining all constructs or dimensions from different instruments used in previous studies allows for a comprehensive assessment of all SRL aspects. This highlights the strength of self-reported questionnaires in aligning with theoretical SRL components. However, we acknowledge their limitations, as Winne and Perry (2000) describe self-report data as an aptitude-based SRL measurement. The issue is that, although these tools accurately reflect SRL components, they rely on respondents’ perceptions or beliefs, which can introduce subjective biases.

In contrast, event-based measurement offers more objective data by recording actual learning events through manual traces or system logs, such as LMS or MOOC interaction data. Nevertheless, this method faces its own challenge of directly linking specific activities to SRL components. Therefore, we recommend using a combination of both aptitude-based and event-based SRL measures.

Our review also showed that many studies documented data collection through assessments. Most do not explicitly state that assessment scores directly measure SRL; instead, they generally evaluate SRL using quantitative questionnaires and analyze the relationships between these scores and assessment outcomes. While this pattern is expected, it provides valuable insights because the primary goal of SRL enhancement is to boost students' learning or academic performance, aligning with the broader research framework of SRL (Schunk & Greene, 2018). Additionally, we noticed that, although smaller in scale compared to questionnaires and assessment data, information system logs are used to measure SRL. This approach could be potentially applied in online learning, particularly by utilizing learning analytics and educational data mining methods. For instance, Araka et al. (2020) emphasize that analyzing learning traces from logs helps measure and serve as indicators for supporting interventions. A practical example is student-facing LADs that display learning indicators and help students monitor their progress (Van Leeuwen et al., 2022). Later, we will examine how these measurements relate to interventions, including their potential benefits and challenges.

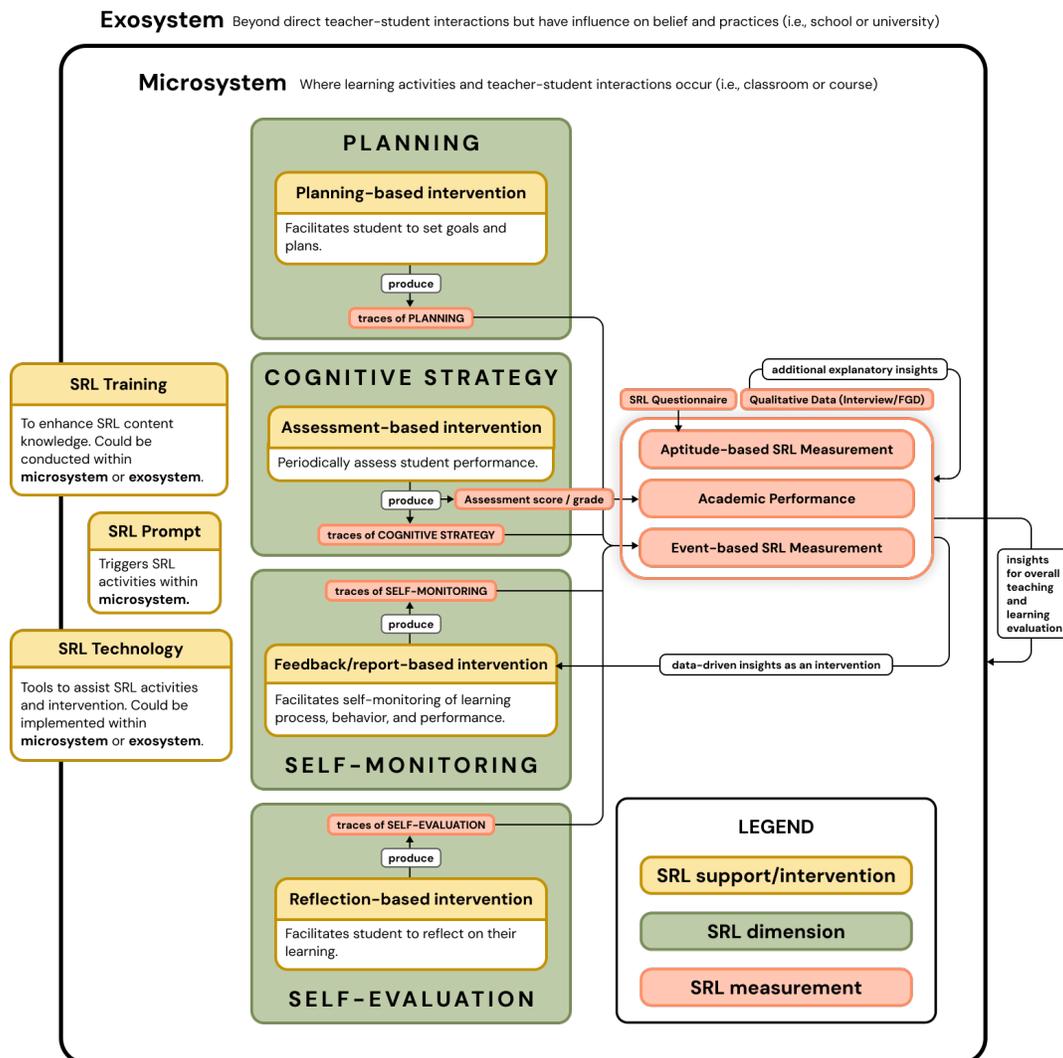
Apart from these three measurement categories, other types, such as interviews, focus group discussions, and open-ended questionnaires, were seldom found in the reviewed articles. Using solely qualitative data for measurements, as mentioned by Winne and Perry (2000), is expensive and has a risk of bias. However, in return for the higher cost, it provides more profound and more thorough insights. Therefore, we recommend using qualitative methods as secondary measures to provide a more explanatory context and enhance insights from either quantitative or trace measurements.

Regarding RQ3, which addresses the main research gap we aim to fill and aligns with Araka et al.'s (2020) review on the emerging trend of using learning traces from system logs to measure SRL, we observe a clear link between technology-assisted interventions and learning system data. However, integrating these interventions with measurement involves challenges related to data adaptation and contextualization. While system data offer potential solutions, analyzing this data can be costly when mapping it to SRL components (Winne & Perry, 2000). Its usefulness also depends on the specific learning activities in the classroom or learning environment, as using traces as indicators is closely tied to instructional design (Blumenstein, 2020). Although our review did not find a strong link between prompt-based interventions and measurement with learning system data, we see its potential. Teachers and lecturers can encourage students to participate in SRL-related activities within the LMS or learning experience platforms. Similarly, interventions such as planning, reflection, and assessment, which are already linked to SRL components – such as planning-based interventions that support goal setting – can be enhanced by technology. The usage logs generated in these cases can be collected as SRL traces. These logs are automatically recorded in learning system databases and should be straightforward to map onto SRL components because these learning activities are designed to align with them.

Student grades and assessment scores, on the other hand, provide clear insights into academic performance but are limited in terms of SRL insights. In addition to findings that align with Araka et al.'s (2020) review regarding quantitative questionnaires, assessment data emerged as a mature data collection technique. These techniques can be adapted for various interventions and have the potential to enhance the contextualization of questionnaire use. However, neither measurement had a noticeable association with any of the intervention types. This finding, characterized by the high frequency of use but low association with any intervention, can be interpreted to mean that both measurement types were used prior to the intervention, regardless of the type.

Building on the discussion above, we propose an initial SRL support model that incorporates holistic, comprehensive, and technology-enhanced assistance for SRL in higher education. This model is illustrated in Figure 11 and is derived from our research, integration suggestions, and prior review insights, especially those from Araka et al. (2020). In line with Araka et al.'s (2020) findings on using learning traces from system logs to evaluate SRL, we observe a strong connection between technology-supported interventions and learning system data. Additionally, we adopt Alvi and Gillies' (2020)

definitions of the microsystem (i.e., classroom or course) and exosystem (i.e., school or university). Along with the model, we offer practical implications and recommendations.



**Figure 11. Initial holistic, integrated, and technology-assisted SRL support model in higher education**

First, SRL training can support the overall students’ SRL knowledge (Theobald, 2021). SRL prompt should be applied in the existing learning activities to trigger overall SRL-related activities (Ifenthaler, 2012). Dimension-specific interventions, such as planning-based and reflection-based interventions, can be embedded in a learning activity. Periodic assessment, for example, with formative assessment, can support students’ self-assessment of their performance and cognitive strategy (Clark, 2012). Feedback and reports, for instance, through student-facing LADs, can facilitate students to do self-monitoring of their learning (Van Leeuwen et al., 2022).

All of those interventions, without the help of technology, would be simply interventions. While their effect on SRL can be measured using quantitative questionnaires, and scores or course grades can assess the impact on academic performance, these measurements fall under SRL measures in terms of ability (Winne & Perry, 2000). These assessments rely on students’ self-perceptions of their own state. In practice, neither self-report data nor assessments truly capture students’ SRL processes or

their moment-to-moment states. Although we can collect data periodically, it is limited compared to the data gathered by event logs in e-learning environments or learning tools. Therefore, incorporating learning technology into SRL interventions should improve event-based SRL measurement, offering additional, more process-oriented, and temporal insights into SRL (Siadaty et al., 2016). This also allows for advanced analysis, including learning analytics, educational data mining techniques, and machine learning (Araka et al., 2020). The measurement can function not only as a basic indicator of the success of SRL interventions but, as Araka et al.'s (2020) review notes, it can also be displayed to students through data visualizations or dashboards, enabling them to track their overall learning behavior, processes, SRL, and their level of regulation.

Based on this model, we recommend that different stakeholders in higher education institutions take practical steps. First, all microsystem activities require participation from teachers, who facilitate learning and serve as the primary agents of SRL (Kramarski, 2017). Since lecturers often face time and skill constraints, they need support through training or technology (Agbenyegah & Geduld, 2024; Faza & Lestari, 2025). Multiple studies (e.g., Bruna et al., 2023; Dignath, 2021) demonstrate that SRL training programs effectively enhance competency and self-efficacy, thereby encouraging SRL. Therefore, higher education institutions should implement such programs to support teachers.

Additionally, SRL training benefits students by enhancing their SRL strategies and academic performance (Theobald, 2021). Second, SRL prompts can motivate students to engage in self-regulation. Teachers and instructional designers should create activities that help students reach learning goals while also developing their self-regulation skills. Activities that generate traces can serve as event-based SRL measures, although recording these can be challenging without the right tools. Higher education institutions should provide learning platforms like LMS or specialized tools designed to support SRL, such as goal-setting apps, electronic diaries, and LADs that track usage logs. These logs, combined with learning analytics and educational data mining, can offer valuable insights and produce data-driven feedback for students and institutions. Incorporating every component may be challenging, especially if there is resistance to change (Faza & Lestari, 2025). Therefore, all stakeholder perspectives should be considered when implementing the SRL support strategy based on this initial SRL support model.

The initial SRL support model already addresses the integrated and technology-assisted aspects of SRL strategies in higher education. However, full involvement of stakeholders – specifically teachers or lecturers, students, curriculum designers, and top-level management – has not yet been fully explored. This model also does not yet consider different learning subjects that may vary in instructional design and task type, which, according to Butler and Cartier (2005), could also influence the development of learning activities. That area still requires further investigation, not just through a literature review, but also from teachers' perspectives, such as via interviews, focus groups, or a soft-systems methodology in real-world settings.

## CONCLUSION

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This review of 109 studies published between 2014 and 2023 examines interventions and data collection methods in higher education. The interventions – such as planning-based, reflection-based, training-based, prompt-based, feedback/report-based, and technology-assisted – are often used in combination, demonstrating their combined potential. Feedback- and report-based, along with technology-assisted interventions, have become more common and are frequently combined, highlighting the importance of feedback tools like LADs in improving SRL skills. These findings suggest that SRL research is increasingly integrating technology into interventions, yet no reviews have examined how these interventions relate to measurement approaches when comparing technology-based and traditional methods. Unlike previous reviews that focused solely on either intervention or measurement, this study bridges these two areas, highlighting their connections and addressing the gap in

knowledge about how SRL interventions and measurement relate in both technology-driven and traditional learning environments.

We acknowledge that a limitation of this study is its completion date in 2023, which means it does not include the most recent studies available at the time of publication. Additionally, there are potential biases in the QCA, which a single coder conducted. Although we try to minimize potential bias by defining a detailed and descriptive coding framework, and the analysis was periodically reviewed and approved by all authors, these biases remain a concern.

This study also proposes an initial model for a holistic, integrated, and technology-assisted approach to SRL support in higher education. The initial SRL support model utilizes SRL training and prompts to establish foundational knowledge of SRL. Technology can facilitate dimension-specific interventions by capturing SRL-relevant learning activity traces through system logs. System logs measure SRL events, while self-reports measure SRL aptitude. Qualitative data and assessment data provide further insights into SRL and its relationship with academic performance. Future research will focus on validating the initial SRL support model using qualitative methods, expert opinions, and the development of an integrated measurement dashboard system.

Although this model needs validation through field insights, some practical recommendations can be implemented in the learning environment at the microsystem (e.g., classes, courses) and exosystem (e.g., curriculum, departmental programs, faculty, or universities) levels. To support SRL, lecturers should be equipped with pedagogical and content knowledge to teach SRL concepts and practices effectively. This knowledge can be acquired independently or integrated into an exosystem program. In classrooms, prompts can encourage students to practice SRL activities. If SRL activities are conducted without tools, recording traces becomes difficult, making it less sustainable. Conventional environments also have a limited capacity to measure SRL events. Nonetheless, SRL assessments via questionnaires can be given at the start and end of the year to gauge students' SRL profiles and progress. Higher education institutions with LMS can use system logs to generate learning traces, which are relevant only if prompts trigger SRL activities. Advanced analysis, combining data types with learning analytics and data mining, produces insights to evaluate learning activities and provide personalized feedback, displayed through reports or dashboards.

This study provides a foundational overview of SRL support in higher education, highlighting a shift toward integrated, technology-enhanced interventions. The review emphasizes the potential of combining approaches, especially feedback- and technology-based tools. It highlights the importance of utilizing both system logs and self-reports to comprehend SRL. By sharing knowledge and leveraging technology, higher education can adopt a sustainable, data-driven approach to help students become self-regulated learners.

Future research should focus more on gathering insights from various stakeholders in real higher education settings to validate the initial model synthesized from this study. Including real stakeholders' perspectives could make our initial model more validated and relevant, especially regarding holistic, integrated, and technology-assisted support for SRL.

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## APPENDIX: LIST OF REVIEWED ARTICLES

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