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Features and Strategies of Adaptive Learning Analytics Dashboards for Supporting Self-Regulated Learning: A Systematic Literature Review

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Abstract

This systematic review investigates the features and strategies of adaptive learning analytics dashboards (LADs) that support self-regulated learning (SRL), mapping them to its metacognitive, motivational, and behavioural components. This mapping is intended to strengthen students' SRL skills. Using the Kitchenham method (2004), the study systematically analyzes 69 articles published from January 2019 to October 2024 through the planning, conducting, and reporting stages. Of these articles, 25 concern conventional LADs and 44 concern adaptive LADs implemented to support SRL. The findings indicate that the adaptive characteristics of LADs help students decide what action to take after analyzing their learning data. Recommended adaptive LAD features include goal-setting, progress tracking, self-assessment, feedback mechanisms, and performance prediction. These features promote monitoring and reflection, which may improve student motivation and active engagement. Future research should analyze adaptive LAD features that support SRL components in greater depth and use longitudinal designs to examine the effects of adaptive LADs on students' SRL abilities.

Notes for Practice

- Compared to conventional LADs, adaptive LADs offer distinct advantages in enabling early, targeted interventions and delivering timely feedback to students, because they use real-time student data.
- Recommended features of adaptive LADs that support student self-regulation include goal-setting, progress tracking, analytics reporting, self-assessment tools, feedback mechanisms, and performance prediction.
- Self-assessment features could help students reflect on their understanding of course topics, their performance, and their learning activities throughout the course.
- Adaptive LADs also enable teachers to refine instructional strategies and support more individualized learning paths by analyzing students' real-time learning progress and outcomes.
- Teachers are encouraged to use student self-assessment outputs as a reflective tool for their own instructional design, adjusting teaching strategies based on patterns revealed in student self-reflection data.

Keywords: Adaptive learning analytics dashboard, learning analytics dashboard, self-regulated learning, systematic review

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1. Introduction

Self-regulated learning (SRL) is a process in which students actively regulate their learning to achieve their goals (Zimmerman, 2002). Zimmerman's SRL model identifies three phases: forethought, performance, and self-reflection. In forethought, students analyze goals and tasks, as well as strategies for achieving them. In performance, students implement the strategies they have developed and continuously assess their effectiveness in achieving their goals. In self-reflection, students reflect on their strategies and determine their next course of action. Across these three phases, the main areas of regulation are cognition, metacognition, motivation, and behaviour, which are interrelated (Pintrich, 2004).

SRL has a significant positive impact on students in secondary and higher education, where learning requires complex thinking processes. With SRL, students can improve their understanding of the material by adjusting their learning pace based on their abilities while maintaining a focus on classroom learning objectives. However, existing research indicates that students still struggle to become self-regulated learners, beginning with identifying their learning needs and setting appropriate goals (Karlen et al., 2020). This difficulty stems from uncertainty about how to identify their learning strengths and weaknesses and relates to metacognition, the ability to recognize and understand one's thought processes.

Moreover, students still struggle to monitor their progress and adjust their learning strategies as required. They may not know what to monitor or what actions to take on the basis of that monitoring. Through SRL, however, students learn what to monitor and how to act by reflecting on their learning experiences. Students' motivation to improve their learning and understanding is also crucial for effective self-regulation. High motivation further encourages them to act and practise self-regulation.

To address students' challenges with self-regulation, schools and universities use tools such as learning analytics dashboards (LADs), which can present students with their learning progress to help them become more aware of it (Yousef & Khatiry, 2023; L. Zheng et al., 2022). Learning analytics is the collection, analysis, interpretation, and communication of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching (Society for Learning Analytics Research [SoLAR], 2025). Unlike other analytics or feedback tools, such as recommendation engines or automated alert systems, LADs are specifically characterized by their visual data representation, interactivity, and direct accessibility to learners within the learning environment (Schwendimann et al., 2017; Verbert et al., 2014). LADs analyze learner data to support the interpretation of progress, performance, and learning outcomes, thereby improving the learning environment and experience (Arnold & Sclater, 2017; Mougiakou et al., 2023). The interactive and comprehensible nature of LADs helps students become aware of their current progress in relation to classroom or independent-learning targets and outcomes. Teachers can also view this dashboard to receive early warnings about their students' learning progress.

However, in practice, a dashboard that only displays this type of student data is insufficient, as not all students have strong self-regulation skills that enable them to immediately determine appropriate actions based on the data displayed on the dashboard. Furthermore, through a conventional LAD, the impact on student self-regulation is not sustained because it only increases students' awareness (Jivet et al., 2017). While Jivet et al. (2017) established that LADs can raise student awareness of their learning progress, their work also highlights that awareness alone is insufficient for sustained self-regulation, as students still require guidance on how to act on the information presented to them. Therefore, as proposed by Jivet (2021), LADs that adapt to students' learning competencies are required to help them practise and improve self-regulation. This adaptive dashboard is expected to adjust its features according to students' learning progress and outcomes, for example, by providing recommendations for improvement and feedback on student progress and outcomes (Chernikova et al., 2020).

This study addresses a gap in prior research, where existing studies on LADs and SRL, including those employing open learner models, have tended to focus narrowly on the metacognitive or cognitive dimensions of self-regulation (Hooshyar et al., 2020), while devoting comparatively less attention to the motivational and behavioural components that are equally central to the SRL process, as defined by Pintrich (2004). While established SRL frameworks have long conceptualized metacognition, motivation, and behaviour as interrelated (Pintrich, 2004; Zimmerman, 2000), previous reviews (e.g., Heikkinen et al., 2023; Viberg et al., 2020) have noted challenges in focusing on these three aspects and utilizing them as indicators that facilitate SRL support rather than solely as measurements. As indicators, these aspects also differ in character. Behavioural traces encompass students' observable learning behaviours, such as persistence, help-seeking, and study time, whereas cognition, metacognition, and motivation primarily involve mental and motivational processes (Pintrich & De Groot, 1990). Therefore, this study aims to review LAD-based empirical studies that support SRL across all three components to propose a set of features that can be integrated into adaptive LADs.

To address these gaps, this systematic review first analyzes existing LADs to distinguish their characteristics from those of adaptive LADs, strengthening the positioning of adaptive LADs in supporting students' SRL. Subsequently, this review analyzes previous research to identify features that can be implemented in adaptive LADs to support students' SRL. Furthermore, this study recommends strategies for students' use of adaptive LAD features. Therefore, this study aims to investigate existing LADs and identify the essential features for supporting students' SRL through the following research questions:

RQ1. What types of LADs have been implemented in existing learning platforms to support SRL?

RQ2. What features are recommended for adaptive LADs to support students in the SRL process?

RQ3. What strategies are recommended for using adaptive LADs to enhance students' SRL?

The identified adaptive features of LADs are mapped to the SRL components based on Pintrich's framework of SRL evaluation, which comprises metacognition, motivation, and behaviour. This mapping approach was used because the study aimed to identify which dashboard features support the development of specific self-regulation skills, while remaining conceptually aligned with the process-oriented SRL cycle proposed by Zimmerman. By emphasizing SRL components as foundational skills, this approach acknowledges that learners must strengthen their metacognitive, motivational, and behavioural capacities before effectively engaging in the sequential phases of the SRL process. Specifically, Pintrich's (2004) framework serves as the component structure, defining the metacognitive, motivational, and behavioural dimensions on which adaptive LAD features are mapped, while Zimmerman's (2002) cyclical model provides the process structure, grounding the sequential logic of how students engage in forethought, performance, and self-reflection. Thus, these two frameworks have complementary rather than competing roles in the present study.

2. Review Methodology

This study used the Kitchenham method for conducting a systematic literature review; this method comprises three stages: planning, conducting, and reporting the review (Kitchenham, 2004). In the planning phase, the researchers defined the population, intervention, comparison, outcome, and context (PICOC) analysis from the research question and established a comprehensive review protocol. The review protocol outlined the search strategy, inclusion and exclusion criteria for selecting relevant studies, and article quality criteria. The second phase involved searching the literature using the selected databases to identify potentially relevant studies. These articles were then evaluated using predefined inclusion and exclusion criteria, followed by a quality assessment using the established criteria. Finally, selected articles were systematically categorized to facilitate synthesis, with the information organized as metadata and answers to the review questions. The final phase focused on synthesizing and presenting the review findings in a clear and concise narrative to identify key trends and patterns observed in the existing literature and provide insightful answers to the research questions. Additionally, this stage critically examined the limitations of current research and explored the potential for future research directions in this area.

2.1. Planning

This systematic review used five databases: ScienceDirect, Scopus, SpringerLink, Taylor & Francis, and the Journal of Computer Assisted Learning (JCAL). The timeframe for this review encompassed a period from January 2019 to October 2024. Based on the research question, the researchers employed PICOC analysis to guide the literature selection process and ensure that the selected literature would be relevant to the research topic of LADs, adaptive features, and strategies to optimize the adaptive dashboard functionality.

The literature selection process adhered to three phases: the initiation stage, title and abstract selection, and full-text selection (Kitchenham, 2004). The entire selection process, from database selection and search query formulation to the initial screening and final article extraction, was validated by two independent reviewers who served as raters and were researchers and senior lecturers in educational technology with expertise in computer-assisted learning and SRL. This validation ensured that the selected articles were appropriate and relevant for addressing each research question.

2.1.1. Identifying Review Questions

The researchers employed PICOC analysis to systematically break down the research question into distinct elements (Carrera-Rivera et al., 2022). The PICOC analysis ensured that the literature review was comprehensive and targeted by reducing the broad topics into precise, answerable questions that guided the SLR. This structured approach also enabled the researchers to conduct a focused and efficient search of previous literature using the review questions applied for this systematic review. Table 1 presents a PICOC analysis describing the targeted population, intervention, comparison, outcome, and context of the systematic review topics. These elements helped the researchers define the scope of the systematic review and align the selected literature with the review questions. The selected literature is therefore relevant to the research objectives and addresses the research questions.

Table 1. Research Question Structure Using PICOC

PICOC components	Descriptions
Population	Students as learning platform users
Intervention	Adaptive LADs, learning analytics dashboards, real-time learning analytics
Comparison	Different learning analytics dashboard types, features, and designs
Outcome	Existing LAD types used in learning platforms, recommended features of adaptive LADs, recommended strategies for implementing adaptive LADs to improve the SRL process
Context	Learning platforms with implemented LADs

2.1.2. Identifying Database Sources

The researchers selected five database sources for the literature search: ScienceDirect, Scopus, SpringerLink, Taylor & Francis, and JCAL from Wiley Online Library. SpringerLink and Taylor & Francis were selected because many of their articles focus on education and educational technology. ScienceDirect was selected to provide articles from educational and technological perspectives. JCAL was specifically selected because it consistently publishes research on educational technology design and evaluation, with a strong emphasis on the pedagogical use of learning analytics systems, dashboards, and feature-level analysis that aligns with the focus of this study. JCAL articles frequently investigate how technological features support learning processes, reflection, and instructional decision-making, making the journal particularly relevant as a design-oriented reference for this research. Finally, Scopus was also used to ensure broader coverage and capture relevant studies published outside the other databases, minimizing the risk of publication bias.

The researchers used the words "learning analytics," "learning analytics dashboard," "adaptive," "self-regulated learning," "feature," and "strategy," as well as synonyms of these words, to capture related articles that could provide insights to address the review questions. The combinations of the keywords "learning analytics" and "learning analytics dashboard" differed across databases and were adjusted according to the results obtained to ensure comprehensive coverage while maintaining relevance to the research context. In Taylor & Francis and JCAL, the combination ("learning analytics dashboard" OR "learning analytics") was used to capture papers discussing learning analytics in general, including those that implicitly mention dashboards without the explicit phrase "learning analytics dashboard." In SpringerLink, the keyword "learning analytics dashboard" was used alone because it already yielded papers focused on LAD without the need to add an OR with "learning analytics." Meanwhile, in ScienceDirect, which limits the search to a maximum of 8 words, more relevant results were found using the single keyword "learning analytic" rather than "learning analytics." In addition, the intentional selection of keywords in this review was influenced by previous systematic reviews, which often relied on limited keywords, such as only using "learning analytics" and "self-regulated learning." That approach failed to capture literature using synonyms of these terms (Matcha et al., 2020; Valle et al., 2021).

The Boolean queries used for each database, shown in Table 2, were tailored to each database source. The researchers adjusted the queries by incorporating synonyms, depending on the number of articles retrieved. To maintain consistency across the database searches and ensure that the context of the search remained aligned, the researchers applied the same combination of Boolean operators ("AND" and "OR") across all databases (MacFarlane et al., 2022).

Table 2. Boolean Search Queries for Database Sources

Database	Boolean Queries
Scopus	("learning analytic" OR "dashboard") AND ("adaptive" OR "personalize" OR "feedback") AND ("metacognition" OR "metacognitive" OR "self-regulation" OR "self-regulated" OR "cognitive") AND ("feature" OR "tool" OR "visual" OR "component" OR "attribute" OR "design") AND ("improve" OR "increase" OR "enhance" OR "strategy" OR "strategies")
ScienceDirect	("learning analytic" AND "dashboard") AND ("adaptive" OR "personalize") AND ("metacognition" OR "self-regulation") AND ("strategy" OR "feature" OR "design")
Springer	("learning analytics dashboard") AND ("adaptive" OR "personalize" OR "feedback") AND ("metacognition" OR "metacognitive" OR "self-regulation" OR "self-regulated") AND ("feature" OR "tool" OR "visual" OR "design") AND ("improve" OR "increase" OR "promote" OR "enhance") AND ("strategy" OR "strategies")
Taylor & Francis	("learning analytics dashboard" OR "learning analytics") AND ("adaptive" OR "personalize" OR "feedback") AND ("metacognition" OR "metacognitive" OR "self-regulation" OR "self-regulated") AND ("feature" OR "tool" OR "visual" OR "design") AND ("improve" OR "increase" OR "promote" OR "enhance") AND ("strategy" OR "strategies")
Journal of Computer Assisted Learning	("learning analytics dashboard" OR "learning analytics") AND ("adaptive" OR "personalize" OR "feedback") AND ("metacognition" OR "metacognitive" OR "self-regulation" OR "self-regulated") AND ("feature" OR "tool" OR "visual" OR "design") AND ("improve" OR "increase" OR "promote" OR "enhance") AND ("strategy" OR "strategies")

2.1.3. Study Selection Strategy and Criteria

The study selection criteria were designed to ensure that only relevant and qualified studies are selected to address the review questions, which are related to LADs and SRL. Table 3 presents the inclusion and exclusion criteria for the initiation stage, title and abstract selection, and full-text selection.

The inclusion criteria primarily focused on covering literature published between January 2019 and October 2024, journal articles and conference papers, literature published in English, and studies focusing on LADs or SRL. This publication period was selected because it represents the most recent and relatively mature developments in LAD research in the context of rapidly evolving technologies. Older studies may reflect design patterns and technological assumptions no longer relevant to current dashboard implementations. Journal articles and conference proceedings were included to achieve comprehensive coverage of the literature, as learning analytics research is often published through both types of publications. The exclusion criteria included papers that did not discuss LADs and SRL, as well as those that did not discuss the features, elements, components, or functionality of LADs, to focus the review on relevant papers.

Table 3. Inclusion and Exclusion Criteria

Stages	Inclusion criteria	Exclusion criteria
Initiation stage	• Published 2019–2024 • English • Research article	• Duplicates • Published before January 2019 and after October 2024 • Non-English papers • Review papers
Title and abstract selection	• Focuses on LADs and adaptive dashboards • Mentions learning platforms • Focuses on metacognitive skills, self-regulation, and SRL	• General learning analytics not mentioning LADs and adaptive dashboards • Does not address metacognition or SRL • Focuses on technical aspects or system architecture of learning analytics
Full-text selection	• Provides empirical evidence on the implementation of adaptive LADs • Identifies LAD features and functionality • Proposes or evaluates strategies to improve SRL through LADs	• Does not address existing LADs used on learning platforms • Does not address LAD features, tools, or design • Does not address strategy or recommend strategies to improve SRL through LADs

After selecting the literature using inclusion and exclusion criteria, the researchers conducted study-quality assessments to evaluate the credibility of each study and the degree to which it contributed to answering the review questions. The quality assessment was conducted to minimize bias arising from systematic errors that could cause results to deviate from the true findings. If a study is free from bias, its results are considered internally valid, meaning the study design and conduct effectively prevent systematic errors (Kitchenham, 2004). Table 4 lists the quality assessment criteria for the selected full-text articles before extraction to answer each research question. The researchers used eight assessment criteria from Kitchenham and Charters (2007), which evaluated the study's research objectives, methodology, data collection method, data analysis techniques, findings, relevance to the research questions, and journal rankings. The quality assessment checklist used scales from 0 to 1, with a value close to 1 if the study met the criteria, and 5 points as the threshold for categorizing a paper as high quality.

The article screening process, encompassing the initiation phase, title and abstract review, full-text evaluation, and quality appraisal, was conducted by two independent reviewers with expertise in educational technology, particularly in the areas of SRL, metacognition, and learning analytics. Both raters were responsible for verifying that every article passing the screening process met the predefined inclusion and exclusion criteria, which had likewise undergone validation by the two experts. This procedure was implemented to guarantee that the articles selected to address the research questions were criterion-compliant and contextually relevant.

Table 4. Quality Assessment Criteria

Checklist	Description
C1	Does the article describe the research objectives clearly?
C2	Does the article describe the proposed architecture or methodology used?
C3	Does the article include a literature review, background, and research context?
C4	Does the article present related work from previous research to demonstrate its main contribution?
C5	Does the article have research results?
C6	Does the article present conclusions relevant to the research objectives/problems?
C7	Does the article discuss the existing implementation of adaptive LADs, features and functionality of LADs, and recommended strategies to improve the SRL process through using LADs?
C8	Indexed in Scopus (Q1/Q2/Q3/Q4/unindexed/conferences)?

2.2. Conducting Literature Selection

Figure 1 shows the flow diagram for the paper selection process, which comprises the initiation stage, title and abstract selection, full-text selection, and quality assessment. The search using the Boolean queries in Table 2 yielded 475 articles, which were then selected using the inclusion and exclusion criteria in Table 3. The initiation stage resulted in 412 studies, the title-and-abstract selection stage resulted in 138 studies, and the full-text selection resulted in 70 studies. After the full-text selection, a quality assessment was conducted using the quality criteria shown in Table 4, resulting in a total of 69 studies that passed the quality criteria.

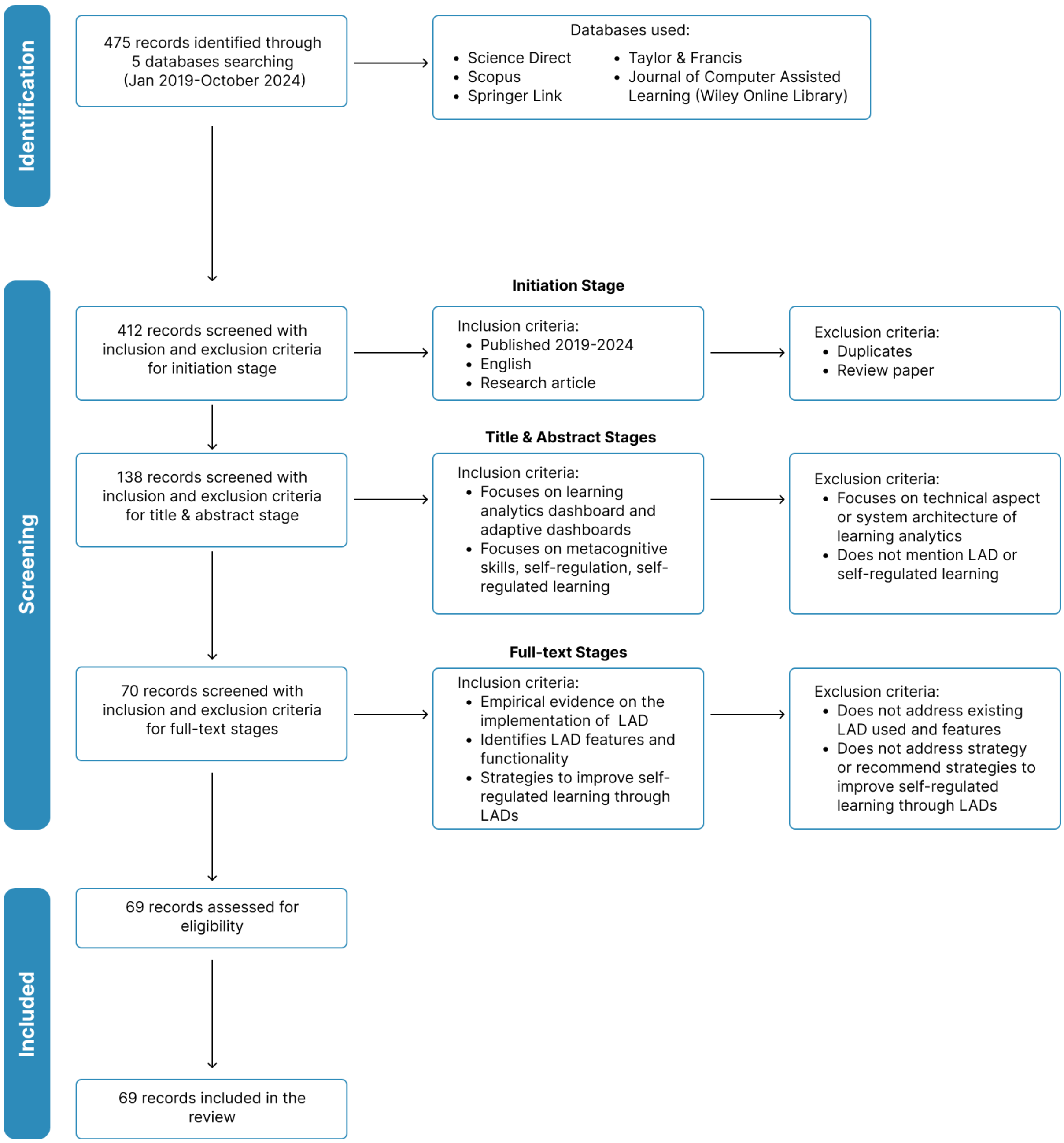

Figure 1. Flow Diagram of Literature Selection

2.3. Summarizing and Reporting Findings

Selected literature passing the quality assessment criteria was extracted based on its title, origin country, study aims, data collection technique, applied framework/theory/methodology, findings, limitations, and future research. Furthermore, the researchers used information from the literature to address the research questions, which involved identifying LAD types (adaptive and nonadaptive), features, and functionality of adaptive dashboards, and strategies for using the features of adaptive dashboards. The researchers then synthesized these data to discover research trends over the years and those based on the origin country. The data extraction results also helped the researchers identify emerging themes and issues requiring further study. Based on these data, the researchers identified gaps in the existing literature to provide future directions for this research area.

3. Findings

Figure 2 shows the number of selected articles included in the review. The figure indicates that the selected literature mainly originated from SpringerLink and Taylor & Francis, with 16 papers each. ScienceDirect had the next-highest number with 15 papers, followed by Scopus with 13 papers and JCAL with nine papers. Research articles from SpringerLink primarily focused on technology-mediated learning strategies, while papers from Taylor & Francis primarily discussed personalized and collaborative learning that could be assisted by LADs. Moreover, the papers from ScienceDirect and Scopus were similar to those from Taylor & Francis, also emphasizing students' motivation and engagement. Finally, papers from JCAL primarily focused on LADs and learning analytics, which are related to SRL processes. The differences in the main focuses of these five database sources assisted the researchers in discovering different perspectives of learning that implement SRL aspects, even if they were not explicitly mentioned in the paper. This also helped the researchers determine the relationships between LAD use and aspects of SRL, including metacognition, behaviour, and motivation.

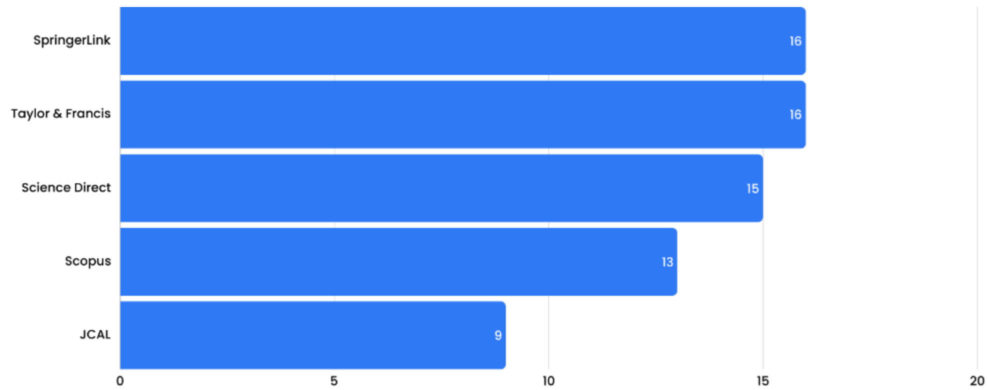

Figure 2. Articles from Five Research Databases

We also identified the countries of origin of the selected articles. The largest number of articles originated in the Netherlands, with 11 papers, indicating substantial Dutch research activity on SRL and LADs. The researchers discovered that the Netherlands' prominent position may be related to its well-developed digital infrastructure, which facilitated the implementation and evaluation of technology-enhanced educational interventions, including LADs. Furthermore, the country's strong culture of open educational resources may also have fostered the development and dissemination of innovative learning tools (Ackermans et al., 2025; De Bruijn-Smolders & Prinsen, 2024; Krishnan et al., 2024).

The second-highest number came from China, with seven papers, followed by Australia, with five. Kılıç and İzmirli (2024) discuss how European countries and China have invested in technology and research; thus, most of the research originates from these two regions. Meanwhile, the numbers for other countries remain relatively small, with between one and three papers each. This pattern may indicate an opportunity to conduct LAD research in additional countries and to analyze how LAD requirements vary with national learning models and needs.

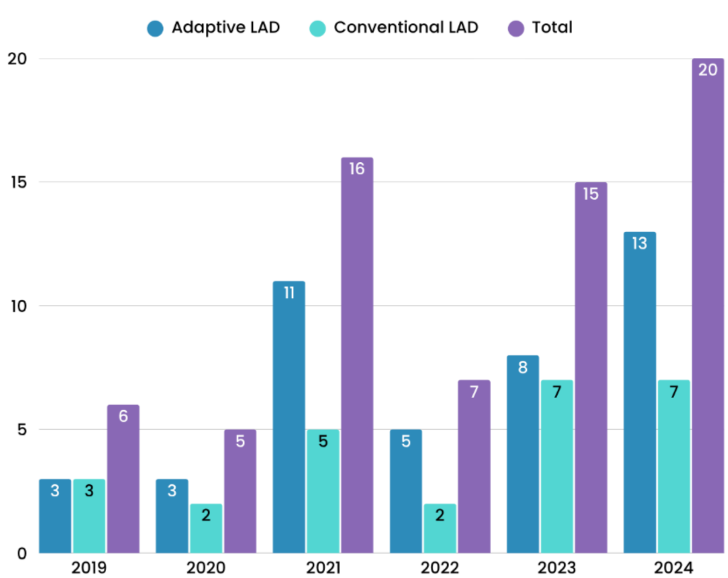

Figure 3. Articles by Year of Publication

Figure 3 illustrates an overall increase in publications related to LADs and SRL. The review included six articles from 2019, five from 2020, 15 from 2021, seven from 2022, 15 from 2023, and 20 from January to October 2024. This surge probably reflects the increased demand for LADs following the shift toward remote and online learning during and after the COVID-19 pandemic (Karaoglan Yilmaz, 2022; Matcha et al., 2020; Yousef & Khatiry, 2023). This trend is further supported by the need for LADs as supportive learning tools within specific learning models, including blended learning (Chen, 2024; De Bruijn-Smolders & Prinsen, 2024), hybrid learning (Lu & Zhang, 2024), and flipped classrooms (Ustun et al., 2023). Educational research published from 2021 to 2024 also indicates a heightened focus on investigating student learning behaviour (Silva et al., 2021; Wan et al., 2023; Xu et al., 2023), collaborative learning processes (Er et al., 2021a; Liebendörfer et al., 2023; L. Zheng, 2021), and the integration of technology to support learning (Mubarak et al., 2022; Valle et al., 2021; Xia & Qi, 2023).

Moreover, research on technology-enhanced learning specifically emphasizes the role of online tools in fostering student interaction and engagement (De Bruijn-Smolders & Prinsen, 2024; Espasa et al., 2022), as well as improving instructional design and teaching methods (Ataş & Yıldırım, 2025). Effective technology integration requires educator adaptation, awareness of technological affordances, and the encouragement of student use for improved learning outcomes (Gelan et al., 2018). Therefore, the potential of LADs as supportive educational tools to improve student and teacher learning processes has increased research attention to LADs as supportive learning tools (Han et al., 2021; Yousef & Khatiry, 2023).

The greater number of studies on adaptive compared to conventional LADs indicates an upward trend in publications focused on adaptive LAD features and strategies for supporting SRL, which may continue beyond the October 2024 review cut-off. Based on previous findings (Han et al., 2021; Joseph-Richard et al., 2021; Tretow-Fish et al., 2023), adaptive LADs are better suited to supporting students' self-regulation skills due to their ability to support student-centred learning, because they facilitate each student's learning process. Students can understand their learning progress and achievements and determine next steps after reviewing the data.

Additionally, adaptive LADs give teachers useful insights regarding student development and performance, enabling them to evaluate and modify teaching methods and instructional practices (Huang et al., 2024; van Leeuwen, 2023). Thus, LADs with adaptive characteristics regarding student data and needs have greater potential than conventional LADs to support and improve student self-regulation skills.

3.1. Addressing RQ1. What Types of LADs Have Been Implemented in Existing Learning Platforms to Support SRL?

LADs were designed to collect, analyze, and visualize educational data to support decision-making processes based on data related to student learning (Han et al., 2021; L. Zheng, 2021). By leveraging data visualization, LADs empower students to monitor their learning progress and performance, aligning their efforts with their learning goals. This fosters students' SRL skills by allowing them to practise planning, monitoring, and evaluating their learning (Alhazbi & Hasan, 2022; Fleur, Marshall, et al., 2023). Meanwhile, for instructors, LADs provide valuable insights into student progress and grades, enabling them to make timely and individualized interventions on the basis of data-driven insights. LADs also support instructors in reflecting on their teaching methods and adjusting their strategies to better meet the needs of their students (Ipinnaiye & Risquez, 2024; Tretow-Fish et al., 2023).

Based on their characteristics, LADs can be categorized into two types: conventional and adaptive learning analytics, depicted in Table 5. Conventional LADs provide a broad overview of student performance, typically presenting aggregated data on overall class performance (Hellings & Haelermans, 2022; Karaoglan Yilmaz, 2022; Park & Jo, 2019; van de Oudeweetering et al., 2024). This includes metrics such as attendance rates, assignment submissions, and examination scores. While conventional LADs are useful for identifying general trends and patterns, they lack the granularity to provide individualized insights. They are often updated periodically, rather than in real time, limiting their ability to support timely interventions.

Conversely, adaptive LADs provide real-time feedback based on individual student progress and behaviour within learning platforms (Chen, 2024; Cheng et al., 2024; Er et al., 2021a; Lim, Gentili, et al., 2021; Sedrakyan et al., 2019, 2020; Wang & Han, 2021; Xu et al., 2025). Adaptive dashboards leverage advanced analytics techniques to identify students who may be struggling or excelling in their learning. By analyzing student data, adaptive LADs can recommend specific learning resources, suggest alternative approaches, or offer timely interventions to help students remain on track.

Table 5. Comparison of Conventional and Adaptive LADs

Characteristics	Conventional LADs	Adaptive LADs
Personalization	Data visualized on the dashboard are the same for all learners.	Learners can customize visualizations of data and metrics based on their needs.
Feedback and recommendations	Do not provide automatic recommendations or suggestions.	Dashboard can provide personalized recommendations based on student data.
Behavioural analysis	Display historical data only, without deeper analysis.	Analyze learning patterns and adjust learning strategies.
Pedagogical interventions	Teachers must analyze student data manually to provide interventions.	Provide automated recommendations to inform teachers' pedagogical decisions.

The literature selected for this systematic review included 44 studies that implemented adaptive LADs to support learning; the remaining 25 studies used conventional LADs, whose features could potentially be adapted to students' learning needs.

A total of 25 articles using conventional LADs showed that they primarily provide information on student progress and performance, helping students and teachers identify behavioural patterns in the learning activities (Hellings & Haelermans, 2022; Hsu et al., 2022; Nguyen et al., 2021; Paredes et al., 2019; Toyokawa et al., 2024; van Leeuwen, 2023). Although conventional dashboards can motivate students to reflect on their activities, they often require teacher guidance to interpret analytics reports from LADs to produce actionable strategies. This limitation underscores the advantage of adaptive dashboards, which provide immediate feedback, enabling a more responsive and effective learning experience.

Conversely, based on the 44 studies that already implemented LADs in learning processes, adaptive LADs could be standalone web applications or integrated into existing learning platforms, offering students and teachers the ability to monitor progress and activities within these platforms. Previous studies (Afzaal et al., 2021; Chen, 2024; Hellings & Haelermans, 2022; Hsu et al., 2023; Lim et al., 2023) demonstrated how an adaptive dashboard provided real-time feedback on student assignments, quizzes, and examination results, enabling learners to immediately identify areas requiring improvement after each test. Using trace data and activity logs, adaptive dashboards generate individualized feedback for each student that can help students remain motivated, engaged, and on their learning trajectories. Teachers can complement this feedback with their insights, creating a synergistic approach that empowers learners and teachers to conduct timely interventions to improve student performance. Adaptive dashboards can enhance students' awareness of their learning progress, particularly in tasks, assignments, and examinations.

Studies by Hellings and Haelermans (2022), Keuning and van Geel (2021), Knoop-van Campen et al. (2024), Sedrakyan et al. (2019, 2020), and Ustun et al. (2023) demonstrate that adaptive dashboards help students easily visualize their progress across multiple assignments, motivating them to refine their learning strategies. Similarly, teachers can monitor student progress and performance, enabling them to provide timely interventions for struggling or disengaged students. Therefore, it can be concluded that adaptive dashboards promote a proactive approach to learning in which continuous feedback aligns learners and teachers with the learning goals.

3.2. Addressing RQ2. What Features Are Recommended for Adaptive LADs to Support Students in the SRL Process?

Adaptive learning dashboards characteristically offer dynamic data-driven features to support students in monitoring their learning progress, evaluating their performance, and receiving timely recommendations for learning strategies based on their performance (Chen, 2024; Cheng et al., 2024; Er et al., 2021a; Lim, Gentili, et al., 2021; Sedrakyan et al., 2019, 2020; Wang & Han, 2021; Xu et al., 2025). These features aim to enhance student engagement with learning activities by increasing course access, encouraging participation in discussions, and promoting help-seeking behaviours with peers and teachers. During the data extraction phase, the researchers categorized LADs into adaptive and conventional LADs based on their characteristics.

After identifying adaptive LADs from 44 articles, the researchers conducted a comprehensive analysis of the features and their functions. This process was challenging, as many articles did not explicitly mention the features, requiring the researchers to carefully infer them by comparing the articles with those that thoroughly described the features and their functionalities.

Table 6. Adaptive LAD Feature Recommendations

Adaptive features	Total studies	References
Goal-setting	27	(Cheng et al., 2024; Eickholt et al., 2022; Farrell et al., 2024; Fleur, Marshall, et al., 2023; Fleur, van den Bos, & Bredeweg, 2023; Fu et al., 2023; Gallagher, Slof, van der Schaaf, Toyoda, et al., 2024; Huang et al., 2024; Järvelä & Hadwin, 2024; Keuning & van Geel, 2021; Kleimola et al., 2025; Knoop-van Campen et al., 2024; Lim, Gentili, et al., 2021; Molenaar et al., 2020; Osakwe et al., 2023; Ouyang et al., 2024; Park & Jo, 2019; Sedrakyan et al., 2019, 2020; Tepgec et al., 2025; Tretow-Fish et al., 2023; Valle et al., 2021; Villagrán et al., 2024; Wang & Han, 2021; C. Yang et al., 2025; Y. Yang et al., 2024)
Analytics reports	8	(Ifenthaler et al., 2023; Jääskelä et al., 2021; Karaoglan Yilmaz & Yilmaz, 2021; Karaoglan Yilmaz, 2022; Nguyen et al., 2021; Tepgec et al., 2025; Wang & Han, 2021; Yılmaz, 2020)
Progress tracking	15	(Alam et al., 2023; Cha & Park, 2019; Eickholt et al., 2022; Farrell et al., 2024; Gallagher, Slof, van der Schaaf, Toyoda, et al., 2024; Hellings & Haelermans, 2022; Hsu et al., 2023; Huang et al., 2024; Karaoglan Yilmaz, 2022; Keuning & van Geel, 2021; Kleimola et al., 2025; Tretow-Fish et al., 2023; van de Oudeweetering et al., 2024; Yan et al., 2021; J. Zheng et al., 2021)
Self-assessment	4	(Berková et al., 2024; Ifenthaler et al., 2023; Xu et al., 2025; Y. Yang et al., 2024)
Feedback mechanisms	27	(Berková et al., 2024; Chen, 2024; Er et al., 2021b; Ez-zaouia et al., 2020; Fan et al., 2021; Fleur, Marshall, et al., 2023; Fu et al., 2023; Gallagher, Slof, van der Schaaf, Toyoda, et al., 2024; Hsu et al., 2023; Jääskelä et al., 2021; Karaoglan Yilmaz, 2022; Liao & Wu, 2022; Lim, Dawson, et al., 2021; Lim, Gentili, et al., 2021; Maheshi et al., 2024; Molenaar et al., 2020; Paredes et al., 2019; Sedrakyan et al., 2019, 2020; Tepgec et al., 2025; Topali et al., 2025; Toyokawa et al., 2024; Valle et al., 2021; Villagrán et al., 2024; Wang & Han, 2021; Xu et al., 2025; Yan et al., 2021)
Performance prediction	9	(Deng et al., 2019; Fleur, Marshall, et al., 2023; Hellings & Haelermans, 2022; Ifenthaler et al., 2023; Joseph-Richard et al., 2021; Kaur & Chahal, 2024; Liao & Wu, 2022; Toyokawa et al., 2024; van Sluijs & Matzat, 2024)

Consequently, the researchers categorized the adaptive features into six distinct types, presented in Table 6. Key features of adaptive dashboards include goal-setting, analytics reports, progress tracking, feedback mechanisms, self-assessment tools, and performance prediction.

Feature mapping is applied to SRL aspects rather than SRL processes because the implementation of planning, monitoring, and reflection relies on the regulation of cognition, metacognition, motivation, and behaviour, which interact with one another. While SRL processes describe the temporal sequence of regulation, SRL aspects represent the core mechanisms being regulated. This approach aligns with Pintrich's (2004) conceptual framework, which emphasizes that SRL measurement and support should focus on these regulatory areas to enable effective enactment of SRL processes.

The frequencies in Table 6 indicate that previous research has most often discussed goal-setting and feedback mechanisms, followed by progress tracking. By contrast, few articles discuss self-assessment features for students, analytics reports, and performance predictions. This suggests future research should explore additional LAD features that can support the SRL process.

Goal-setting features help students define their personal learning objectives and develop effective time management strategies (Kleimola et al., 2025; Knoop-van Campen et al., 2024; Molenaar et al., 2020; Nguyen et al., 2021; Sedrakyan et al., 2019). This can foster a sense of direction and motivation for students throughout the learning process by establishing goals before beginning the learning process. Subsequently, analytics reports on the adaptive dashboards should help teachers automatically generate reports based on student data collected throughout the course (Jääskelä et al., 2021; Karaoglan Yilmaz & Yilmaz, 2021; Nguyen et al., 2021). These reports include frequency of access to course materials, assignment completion rates, quizzes and examination scores, and participation in discussion forums, which can provide teachers with valuable insights into their students' performance.

Features for monitoring students' progress enable learners and teachers to track learning activities, assignment completion, quizzes, and examinations taken in real time (Eickholt et al., 2022; Fan et al., 2021; Karaoglan Yilmaz, 2022; Keuning & van Geel, 2021; Knoop-van Campen et al., 2024; Lim et al., 2024; Sedrakyan et al., 2020; J. Zheng et al., 2021). By monitoring and evaluating their progress, students can make informed decisions about their learning strategies, such as revisiting difficult concepts to deepen their understanding or seeking additional support from peers and teachers. Similarly, teachers can use these monitoring tools to remain informed about students' progress throughout the course. This also enables them to provide timely feedback to guide struggling students, which might include students with low engagement or underperforming students. Furthermore, feedback mechanisms facilitate real-time feedback based on student performance (Afzaal et al., 2021; Chen, 2024; Hellings & Haelermans, 2022; Hsu et al., 2023; Lim et al., 2023), making it individualized based on learners' needs.

The LAD can generate individualized feedback using machine learning algorithms to obtain students' current performance, while teachers can add to this feedback based on their evaluation of student performance throughout the course. Teachers could provide feedback that helps students address learning gaps and guides them in reflecting on their learning process, including learning activities and grades (Er et al., 2021b; Kleimola et al., 2025; Maheshi et al., 2024). This interactive approach, where students can request and respond to feedback, fosters a dynamic learning environment and empowers students to take ownership of their learning.

Moreover, self-assessment features enable students to rate their performance using semaphore methods (Berková et al., 2024; Ipinnaiye & Risquez, 2024; Ouyang et al., 2024; Yan et al., 2021), in areas such as their level of understanding of particular topics, assignment completion, and quiz and examination scores. This method uses different colour signs to highlight indicators, which helps students note their learning problems. Teachers can use this information to identify the problem areas and guide students through them. By knowing the problem areas, teachers can also reflect on their teaching methods and instructional design, regarding whether they are effective in helping students achieve their learning goals and improving their level of understanding. Besides key features of adaptive dashboards involving real-time data, the recommended key features of adaptive dashboards are prediction of student performance (Deng et al., 2019; Fleur, Marshall, et al., 2023; Joseph-Richard et al., 2021; Kleimola et al., 2025; Valle et al., 2021; Yan et al., 2021). These features use learners' current performance and prior achievements to identify patterns that may indicate potential difficulties. For example, if a student consistently misses deadlines or struggles with specific types of assignments, the dashboard can flag them as being at risk of academic difficulty. This predictive capability can support immediate interventions, such as course material recommendations, feedback for learning strategies, and feedback for improving their performance. Alternatively, it can alert instructors to proactively intervene and provide timely support to students at risk of academic difficulties or dropout. Ultimately, these predictive features aim to prevent student failure and dropout.

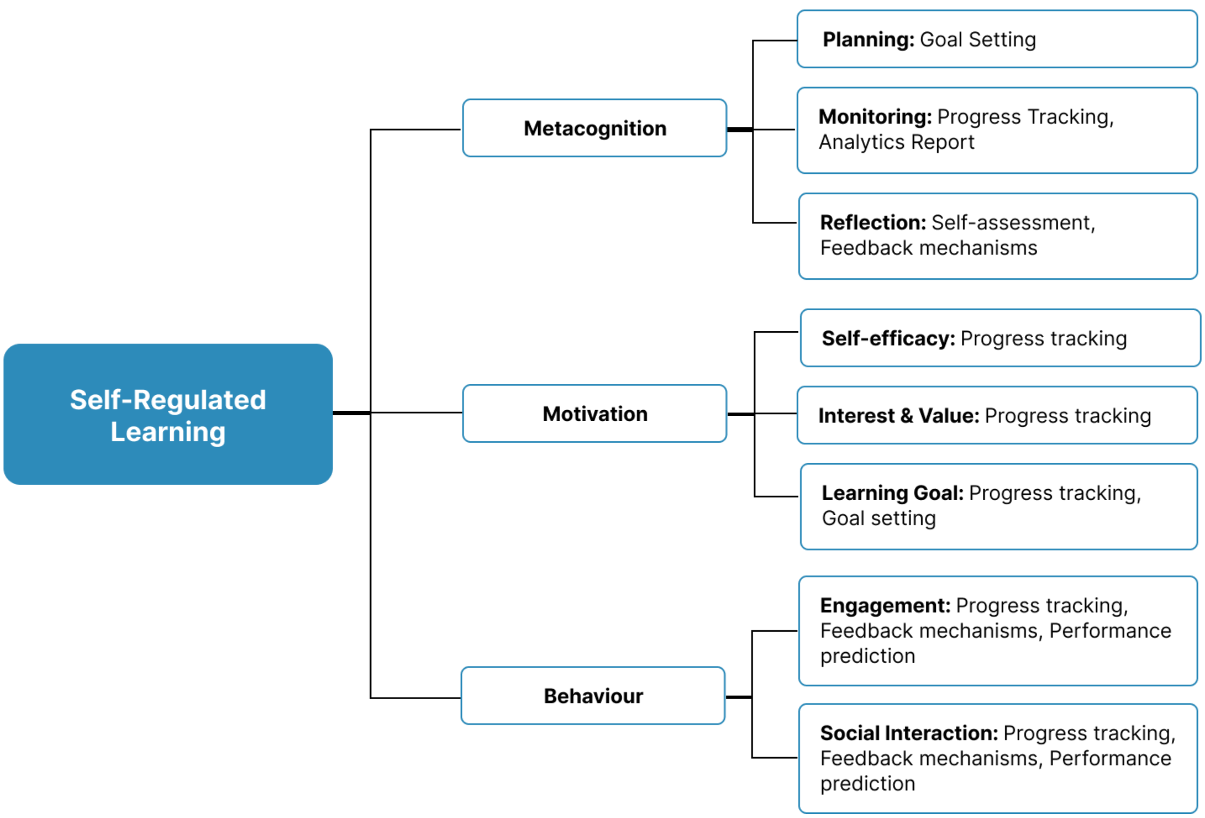

Figure 4. Adaptive LAD Features to Support SRL Processes

The researchers classified the features outlined in Table 6 into the following SRL components: metacognition, behaviour, and motivation, as illustrated in Figure 4. For metacognition, the researchers further divided the metacognitive process into planning, monitoring, and reflection. The planning process is supported by goal-setting, as the features facilitate the establishment of learning goals, which provide direction and maintain student motivation throughout the learning process. The monitoring process is supported by progress tracking and analytics reports, which enable students and teachers to track learning progress and performance. Features supporting the monitoring process should help students assess the effectiveness of their learning strategies, enabling them to adjust and enhance their learning approaches as required (Zimmerman, 2002). The reflection phase of metacognition can be supported by self-assessment and feedback mechanisms. These features enable students to evaluate their learning progress, assess their understanding of the course material, and identify effective learning strategies to implement in subsequent learning processes (Berková et al., 2024; Er et al., 2021b; Lim, Gentili, et al., 2021; Maheshi et al., 2024; van de Oudeweetering et al., 2024).

Self-efficacy, intrinsic interest, and learning value, key components of learner motivation, can be significantly enhanced through effective goal-setting and progress tracking. This is because motivation directly influences goal-setting skills, learning persistence, and the effectiveness of learning strategies, ultimately ensuring learner engagement and resilience when facing challenges (Ackermans et al., 2025; Zimmerman & Schunk, 2001; Zimmerman, 2002). Therefore, beyond supporting metacognition, goal-setting and progress tracking are crucial for fostering intrinsic motivation and supporting successful SRL.

Based on the identification of adaptive LAD features, it can be concluded that to effectively support students in practising SRL, adaptive LADs should incorporate features such as progress tracking, feedback mechanisms, and performance predictions. These features are crucial for helping students practise and strengthen their self-regulation skills, thereby improving their learning experiences (Akçapınar & Hasnine, 2022; Paredes et al., 2019; Yousef & Khatiry, 2023).

3.3. Addressing RQ3. What Strategies Are Recommended for Using Adaptive LADs for Enhancing Students' SRL?

After identifying the adaptive features for LADs and mapping them to the SRL components, the researchers also categorized strategies for implementing adaptive LADs according to the SRL aspects of metacognition, behaviour, and motivation, as shown in Table 7. This categorization was intended to ensure that the strategies aligned with the adaptive features to optimize their effective implementation.

Table 7. Strategy Recommendations for Adaptive LAD Implementation

SRL aspects	Strategies	References
Metacognition	Encourage reflection through visual progress tracking	(Akçapınar & Hasnine, 2022; Deng et al., 2019; Ez-zaouia et al., 2020; Ipinnaiye & Risquez, 2024; Järvelä & Hadwin, 2024; Lim, Gentili, et al., 2021; Sedrakyan et al., 2020)
	Implement self-assessment tools for students to evaluate their learning	(Järvelä & Hadwin, 2024; Park & Jo, 2019)
Motivation	Provide individualized feedback based on student performance	(Er et al., 2021b; Karaoglan Yilmaz, 2022; Yılmaz, 2020)
	Apply gamification elements	(Hu et al., 2024; Yan et al., 2021)
Behaviour	Real-time progress tracking	(Akçapınar & Hasnine, 2022; Karaoglan Yilmaz, 2022; Liao & Wu, 2022; Ustun et al., 2023; Yılmaz, 2020)
	Promote help-seeking through feedback mechanisms.	(Han et al., 2021; Järvelä & Hadwin, 2024)

Adaptive learning dashboards support SRL by focusing on three key components: metacognition, motivation, and behaviour. Metacognitive strategies focus on students' ability to reflect on their learning process and monitor their progress (Akçapınar & Hasnine, 2022; Deng et al., 2019; Ez-zaouia et al., 2020; Ipinnaiye & Risquez, 2024; Järvelä & Hadwin, 2024; Lim, Gentili, et al., 2021; Sedrakyan et al., 2020). Features such as progress tracking, analytics reports, and self-assessment tools enable students to become aware of their strengths and weaknesses in learning. These tools also enable educators to track students' progress and provide timely and targeted feedback tailored to the specific needs of each learner. By leveraging insights from LADs, educators can identify areas where students may be struggling and provide motivational support and additional course resources to help them understand the topics. Moreover, teachers can encourage students to reflect on their learning progress and performance, which can further help students develop a deeper understanding of the subject matter (Järvelä & Hadwin, 2024; Park & Jo, 2019). Feedback from teachers should summarize student progress, highlight areas for improvement, and align with the student's personal learning goals. Such feedback would enhance learner motivation, engagement, and sense of accomplishment. It can also foster a growth mindset, as learners review their progress and recognize the potential for improvement, increasing persistence and resilience in facing learning challenges (Shadiev et al., 2024).

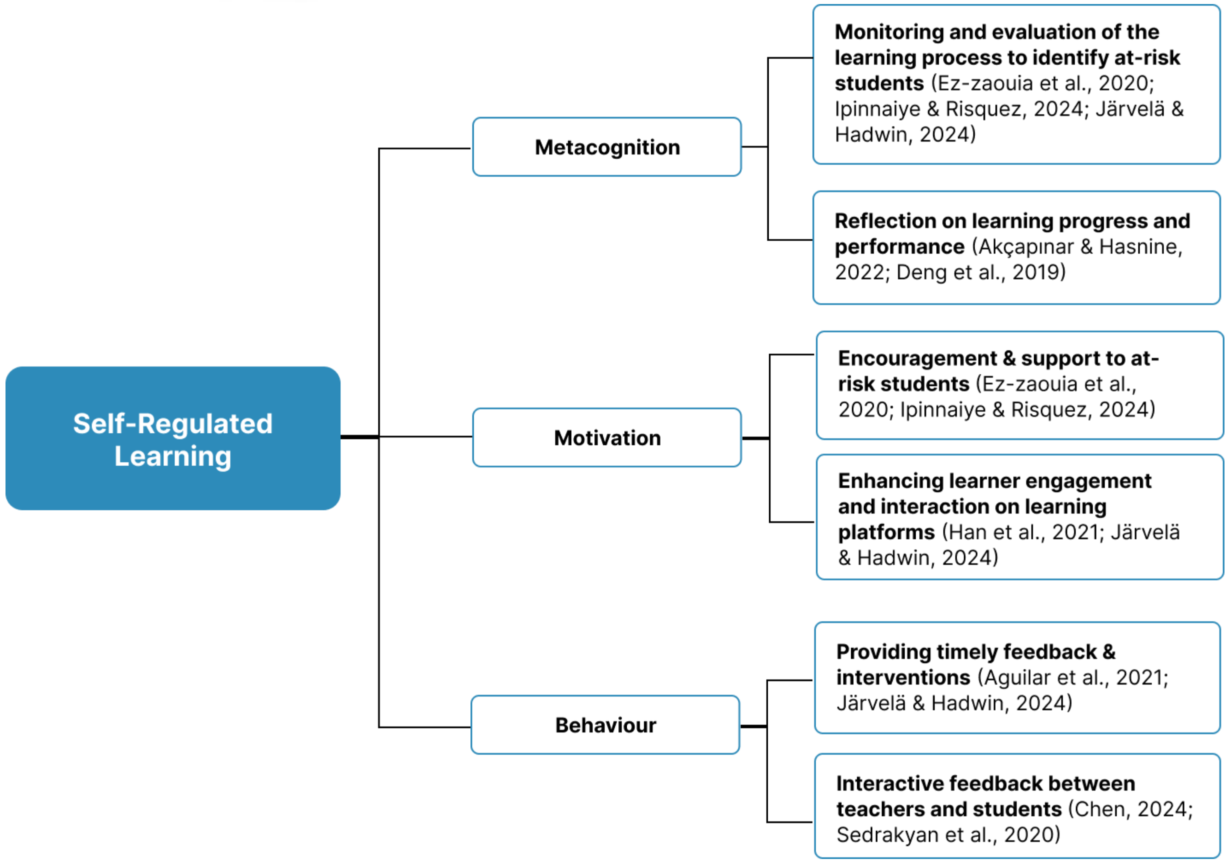

Figure 5. Strategies for Implementing Adaptive LAD Features to Support SRL Processes

Motivational strategies, supported by feedback mechanisms and performance prediction, can be implemented in adaptive learning dashboards to enhance motivation in learning (Aguilar et al., 2021; Järvelä & Hadwin, 2024; Lim et al., 2023; Lim, Gentili, et al., 2021). Gamification elements and multitype visualization can be considered as adaptive dashboard elements that can further enhance student motivation (Hu et al., 2024; Yan et al., 2021). Furthermore, teachers can help sustain student motivation by providing targeted feedback and interventions aligned with their goals that guide them toward their learning goals (Er et al., 2021b; Karaoglan Yilmaz, 2022; Yılmaz, 2020). Teachers can foster a sense of community by encouraging collaborative tasks and peer feedback. Students can therefore motivate and inspire each other by working together, creating a more engaging and effective learning experience.

Behavioural strategies for adaptive learning dashboards can help students engage more fully in the learning process and seek help when facing learning difficulties (Ez-zaouia et al., 2020; Ipinnaiye & Risquez, 2024; Tepgec et al., 2025; J. Zheng et al., 2021). Features such as progress tracking and feedback mechanisms assist teachers in monitoring student progress in real time and promote help-seeking through feedback mechanisms (Akçapınar & Hasnine, 2022; Karaoglan Yilmaz & Yilmaz, 2021; Liao & Wu, 2022; Ustun et al., 2023). Teachers can also encourage students to monitor their learning progress, enhancing their self-regulation and metacognition skills. By encouraging students to seek help, teachers can foster motivation and adaptive learning strategies. Interactive feedback mechanisms in adaptive dashboards can help students become more aware of their learning progress through timely feedback and opportunities to engage with teachers and peers, fostering a collaborative learning environment (Han et al., 2021; Järvelä & Hadwin, 2024).

4. Discussion

This systematic review suggests that publication on LADs may continue to grow because of increased awareness of the need for LADs to support learning processes and improve self-regulation among teachers and students (Fan et al., 2021; Huang et al., 2024; van Leeuwen, 2023). The growth of digital technologies and infrastructure also supports the development of LADs that are adaptive to student needs. Moreover, the increase in publications focusing specifically on adaptive LADs highlights a shift toward the need for personalization in learning processes.

LADs are tools that facilitate the collection, analysis, and visualization of student educational data to assist pedagogical decision-making related to student learning (Gallagher, Slof, van der Schaaf, Arztmann, et al., 2024; Han et al., 2021). Two types of LADs are currently implemented to support SRL: conventional and adaptive. Conventional LADs present an overview

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of student performance and progress that is updated periodically; hence, they primarily support monitoring and evaluation processes for teachers (Akçapınar & Hasnine, 2022; Cha & Park, 2019; Fleur, van den Bos, & Bredeweg, 2023). However, although conventional dashboards can motivate students to reflect on their activities, they often require teacher guidance to interpret analytics reports from LADs to produce actionable strategies (Ramaswami et al., 2023).

In contrast, adaptive LADs can present real-time student data, supporting early and targeted interventions, as well as timely feedback (Eickholt et al., 2022; Tretow-Fish et al., 2023; Villagrán et al., 2024). The findings reveal that adaptive LADs are particularly valuable for fostering SRL by providing features that enable students to set goals, monitor progress, and evaluate outcomes effectively. These tools also equip teachers with insights to improve instructional strategies and support individualized learning paths (Han et al., 2021; Ipinnaiye & Risquez, 2024; Molenaar et al., 2020).

The recommended adaptive LAD features can be effective when used with appropriate strategies. First, students and teachers could use progress tracking to monitor performance through course and material access, assignment submissions, and grades (Berková et al., 2024; Eickholt et al., 2022; Y. Yang et al., 2024). Teachers can use these data to evaluate student assignments and grades to identify at-risk students, such as underperforming and low-engagement students. Teachers could also provide timely interventions and feedback, which encourage students to engage more with the course and materials, as well as participate in discussion forums.

Subsequently, student self-assessment tools help students in reflecting on their understanding of the course topics, their performance, and their learning activities throughout the course. Meanwhile, teachers could use student self-assessment data to reflect on their teaching methods and instructional design, which can help them adjust their teaching strategies for future improvement. Teachers could also encourage students to seek help to deepen their understanding of specific topics and solve problems in assignments and tasks (Ifenthaler et al., 2023; Xu et al., 2025; Y. Yang et al., 2024).

Subsequently, features such as feedback mechanisms and performance prediction can be applied to adaptive dashboards to improve motivation and self-efficacy in learning (Bayazit et al., 2023; Hellings & Haelermans, 2022; Kleimola et al., 2025). Teachers could provide individualized feedback using feedback mechanisms, while also using interactive feedback to discuss suitable learning strategies and recommend course materials that support learning (Akçapınar & Hasnine, 2022; Paredes et al., 2019; Y. Yang et al., 2024). Finally, adaptive dashboards could also implement gamification elements to enhance student motivation to engage more with the adaptive dashboards to regulate their learning process (Lim, Dawson, et al., 2021; Tepgec et al., 2025; Villagrán et al., 2024).

5. Conclusion

This study reveals the features of adaptive LADs that support students' SRL, including goal-setting, progress tracking, analytics reports, self-assessment, feedback mechanisms, and performance predictions. This study also discusses strategies for implementing adaptive features for improving student self-regulation skills, such as monitoring their learning progress and performance, evaluating their learning, and adjusting their learning strategies based on their evaluations.

Based on the findings, the researchers identified limitations in the literature that suggest directions for future research. Future studies should conduct in-depth analyses of adaptive LAD features, transcending general feature descriptions. Researchers are encouraged to systematically identify, categorize, and evaluate adaptive components, such as personalized feedback, dynamic goal-setting, and adaptive visualizations, that tailor dashboard insights to individual learner characteristics. Future studies could employ backward and forward snowballing techniques to establish a more comprehensive and structured taxonomy of adaptive LAD features. Given the emerging interest in adaptive LADs, future work should also explore alternative theoretical foundations beyond SRL, such as cognitive learning processes or domain-specific instructional contexts.

Future research should also adopt longitudinal research designs to examine the sustained effects of LADs on SRL development. As prior studies have primarily captured short-term or momentary impacts, longitudinal investigations are required to validate the long-term influence of adaptive LADs on students' learning processes and academic outcomes.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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