Received: 21 June 2023 | Revised: 8 January 2024 | Accepted: 17 March 2024

DOI: 10.1111/jcal.12982

REVIEW ARTICLE

Journal of Computer Assisted Learning WILEY

Using learning analytics to measure self-regulated learning: A systematic review of empirical studies in higher education

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Funding information
Qatar National Research Fund, Grant/Award Number: RRC02-0731-210013

Abstract

Background: Measuring students' self-regulation skills is essential to understand how they approach their learning tasks in order to identify areas where they might need additional support. Traditionally, self-report questionnaires and think aloud protocols have been used to measure self-regulated learning skills (SRL). However, these methods are based on students' interpretation, so they are prone to potential inaccuracy. Recently, there has been a growing interest in utilizing learning analytics (LA) to capture students' self-regulated learning (SRL) by extracting indicators from their online trace data.

Objectives: This paper aims to identify the indicators and metrics employed by previous studies to measure SRL in higher education. Additionally, the study examined how these measurements were validated.

Methods: Following the protocol of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), this study conducted an analysis of 25 articles, published between 2015 and 2022, and sourced from major databases.

Results and Conclusions: The results showed that previous research used a variety of indicators to capture learners' SRL. Most of these indicators are related to time management skills, such as indicators of engagement, regularity, and anti-procrastination. Furthermore, the study found that the majority of the reviewed studies did not validate the proposed measurements based on any theoretical models. This highlights the importance of fostering closer collaboration between learning analytics and learning science to ensure the extracted indicators accurately represent students' learning processes. Moreover, this collaboration can enhance the validity and reliability of data-driven approaches, ultimately leading to more meaningful and impactful educational interventions.

KEYWORDS
learning analytics, self-regulated learning, systematic literature review, trace data

1 | INTRODUCTION

The widespread of adopting educational technologies in learning and teaching in higher education provides opportunities to collect vast amounts of data on students, their use of the educational materials, the patterns of interactions with these systems, and other footprints. In the context of learning analytics, trace data refers to the digital records or 'traces' that students leave behind as they interact with various components of an online learning environment. This can include data on logins, time spent on different pages or resources, submissions of assignments, participation in discussions. This data represents a valuable source of information for learners, teachers and administrators to enhance the learning process. To harness the potential of these digital footprints, the field of learning analytics (LA) uses computational analysis techniques from data science and artificial intelligence to gain insight on hidden patterns of students' learning activities.

Over the last decade, learning analytics (LA) has evolved significantly to support intelligent learning environments in higher education. It offers new approaches and techniques to analyse and interpret data collected about learners' experience in order to understand their learning behaviours, and accordingly provide necessary personalized interventions to improve their learning. LA is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013).

LA involves extracting meaningful indicators from the trace data, analysing and interpreting them to understand learners' behaviours and provide real-time intervention (Araka et al., 2020). However, the quality of learning cannot be inferred from behavioural data alone; therefore, theories and frameworks from learning science and psychology fields are needed to determine what data should be analysed, as well as to interpret the results afterward. This means that the focus should be on understanding the underlying pedagogy of the learning process, rather than solely on the data and the computational analysis that has been used (Kew & Tasir, 2022; Lodge & Corrin, 2017). Recently, researchers have emphasized the importance of grounding learning analytics within learning science and educational theories, as well as the verification of validity of the analysis process to guide the research and ensure that the results are generalizable and actionable (Fincham et al., 2019; Wise & Shaffer, 2015). Therefore, carefully designed experimental studies will improve the maturity of LA by developing models of how learning works, as well as how LA-based interventions influence students' engagement, and success (Lodge & Corrin, 2017).

In learning science, self-regulated learning (SRL) is an essential conceptual framework that explains how students master their own learning processes and rationalize the variance of student performance in different learning contexts. SRL is defined as the degree to which learners are motivationally, behaviourally, and metacognitively engaged in their learning processes (Zimmerman, 1989). It refers to students' ability to control their own learning process and being aware of their learning progress toward specific goals. Self-regulated students monitor their learning and adjust their behaviours when needed to stay on track toward their academic success. They have the ability to overcome academic challenges and to preserve their resilience despite failures and setbacks (Cassidy, 2016). From an SRL perspective, individual differences in learning do not emanate from their personal limitations in intelligence or diligence; rather, they are related to their self-awareness of their way of learning and strategic knowledge to take corrective actions when necessary (Zimmerman, 2002). Zimmerman and Kitsantas (Zimmerman & Kitsantas, 2014) found SRL to be a predictive feature of student's academic performance and persistence. Moreover, previous research reveals a significant correlation between using SRL strategies and learners' academic performance in higher education (Broadbent & Poon, 2015; Broadbent & Fuller-Tyszkiewicz, 2018). SRL is not a mental intelligence or a skill of academic performance, it is trainable and learnable skill that can be acquired by learner or improved by instructional intervention (Alhazbi, 2014; Russell et al., 2022). Accordingly, SRL interventions can improve students' engagements and enhance their performance (van Alten et al., 2020).

Recently, research on using LA to promote SRL has started to form its own sub-area in LA, and an increasing number of studies have utilized LA to better measure and enhance various aspects of SRL in different learning settings, including online, blended, flipped classroom. Using LA to measure SRL has many advantages over traditional approaches such as self-reports questionnaires and think aloud protocol. When using LA, the learners' behaviour is captured unobtrusively by the LMS, it does not interfere with students' engagement in the course.

There are previous studies that reviewed empirical works of using learning analytics to measure SRL like (Araka et al., 2020) (Viberg et al., 2020), however no previous study examined the technical level of learning analytics, which involves identifying the indicators extracted from learners' log data, and how these indicators are subsequently utilized to understand learners' self-regulation in the context of the theoretical frameworks. This paper presents a literature review of empirical studies in higher education that measure self-regulated learning (SRL) using LA. It identifies various indicators that have been extracted from students' trace data to measure their levels of self-regulation, and maps them to the constructs of SRL within theoretical frameworks. Additionally, it explores how these proposed measurements were validated against theoretical frameworks. The paper sheds light on the gap between theories and practice when using learning analytics. The rest of this paper is structured as follows. Section 2 discusses the background aspects of this topic. Section 3 describes the methodology used to identify and collect related studies. Section 4 presents the results, which are discussed in Section 5. Section 6 presents the study limitations, and Section 7 concludes the study.

2 | BACKGROUND

2.1 | Self-regulated learning (SRL)

There are several prominent theoretical models that provide framework to describe constructs, process and phases of SRL (Panadero, 2017). They commonly emphasize the metacognitive aspect of the learning process, which extends beyond acquiring educational contents and skills to encompass knowledge about one's own cognitive process and the use of the most effective approaches for knowledge acquisition and skill development. Moreover, these models view SRL as a cyclical process that begins with planning and preparing, followed by applying the learning strategies, then evaluating and adapting. According to Zimmerman's model (Zimmerman, 2002), SRL is a cyclical process composed of three phases: forethought phase, performance phase, and self-reflection phase. The forethought phase refers to processes and beliefs that occur before starting to learn, such as goal setting, task analysis, planning, and self-motivation. The performance phase refers to processes during learning, including the use of planned strategies, attention focus, and performance monitoring. The self-reflection phase refers to the processes that occur after learning efforts, such as self-evaluation, and reflection.

Similarly, Winne and Hadwin's model (Winne & Hadwin, 1998) describes SRL as four linked and recursive phases: task definition, goal settings, enacting study tactics, and adapting learning approaches. Pintrich's model (Pintrich, 2000) also views SRL as cyclical process composed of four phases: forethought and planning, monitoring, control, and reaction and reflection. Moreover, motivation is considered an important factor in stimulating and sustaining SRL processes (Panadero, 2017). In Zimmerman's model, motivational beliefs are essential components in the forethought phase that energizes the process and affects the activation of learning strategies.

Academic time management is an important dimension of SRL. It refers to students' efforts to use their time purposefully and efficiently in order to achieve their educational goals (Wolters et al., 2017). While time management is not explicitly identified as a critical component in SRL models, it is considered as part of goal setting, planning, and resource management (Wolters & Brady, 2020). For instance, Zimmerman (Zimmerman, 2002) considers controlling time when learning a crucial process that impacts students' level of achievements. Winne and Hadwin (Winne & Hadwin, 1998) indicate that task definition involves considering time constraints, thus students should take them into account during goal settings and planning stage. Pintrich and Zusho (Pintrich & Zusho, 2002) view time management as an expression of a learner's behavioural regulation. It starts in the first stage by making a schedule for studying and allocating time for different learning activities. In the subsequent phase, learners monitor their time management in order to make necessary adjustments aligned with the task requirements. During the third phase, they regulate their time and effort based on the difficulty of the conducted task. In the final phase, students make judgements on their time management and efforts, potentially making a different decisions regarding time allocation in the future.

2.2 | Self-report questionnaire

Traditionally, self-report questionnaires have been used to assess SRL offline, wherein learners are asked to rate their use of SRL strategies. For instance, the Motivational Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993) is one of the most widely used self-report questionnaires to measure student motivation and learning strategies in traditional face-to-face settings. The MSLQ has 81 items and is composed of two parts: the motivational component and the learning-strategy component. Another example of self-report questionnaires is the Learning and Study Strategy Inventory (LASSI) (Weinstein et al., 1987), which aims to measure students' awareness and use of self-regulation strategies. The LASSI is composed of 77 items grouped into scales that include anxiety, attitude, concentration, information processing, motivation, selecting main ideas, self-testing, time management, test strategies, and using learning resources. Additionally, the Online Self-Regulated Learning Questionnaire (OLSQ) (Barnard et al., 2009) is a self-report instrument designed to measure students' self-regulated learning skills in blended or fully online learning settings. OLSQ is composed of 24 items grouped into six scales that include goal setting, environment structuring, task strategies, time management, help seeking, and self-evaluation.

2.3 | Think-aloud

In contrast to self-report questionnaires, the think-aloud protocol is considered an online measure that does not relay on students retrieving information about their strategies they used from memory. Instead, it requires students to verbalize their thoughts while engaging in learning task. This technique has the potential to capture the dynamic aspects of SRL. The think-aloud has been found to capture SRL processes more accurately and predict learning achievements better than self-report surveys (GREENE & AZEVEDO, 2010). However, this approach is still dependent on learners' interpretation of the strategies they use, which may lead to potential inaccuracies. Additionally, cognitive and metacognitive processes may be activated solely because of the protocol itself, and would not be generated otherwise (Siadaty et al., 2016).

2.4 | LA-based measurements

Over the last several years, the pervasive integration of digital technology into higher education (HE), like the widespread use of learning management systems (LMS), has made it possible to capture learners' actions on the fly through tracing log data, which represents digital footprints that learners leave behind when engaging in learning process. This offers opportunities to measure SRL processes based on what learners do as they study. Although the cognitive and metacognitive states of learners cannot be captured directly, the observed indicators in trace data can be used to provide grounds for inferring learner's cognitive and metacognitive activities. The advantage of this approach is that it allows to capture SRL unobtrusively based on authentic data that identify learning events in students' own context (Siadaty et al., 2016). Moreover, it is found that trace-based measurement can explain self-regularity behaviour and its impacts on students' performance better than self-reporting (Cicchinelli et al., 2018) (Li et al., 2020). This is approach is not affected by learners' biased memory or self-selection bias because data is collected while the student is actively learning (Jovanović et al., 2019). However, LMS collects various data about students' online activities, including times of logins, times of accessing different educational materials, the time of assessments submissions, participations in forums, and more. The main challenge lies in identifying and calculating suitable observable indicators from trace data that accurately represent SRL processes as well as validating the proposed measurement.

3 | METHOD

The objective of this paper is to review previous studies that have utilized learning analytics to measure SRL in higher education based on students' behaviours in the digital learning environment. The objective is to identify the indicators that have been extracted from trace data to measure learner's self-regularity and examine how the proposed measurements have been validated based on theoretical models in the field of learning science.

3.1 | Research questions

This literature review in this study is guided by the following research questions:

Research Question 1: What are the indicators in trace data that have been used to measure SRL?

Research Question 2: How have the interpretations of the proposed measurements results been validated?

3.2 | Literature search strategy

This systematic literature review follows the four-phase flow diagram of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology (PRISMA) (Moher et al., 2009), a widely validated method for reporting in systematic reviews that ensures the quality and transparency of systematic reviews and meta-analyses. It offers a checklist and flow diagram that guide researchers in reporting their methodology and findings comprehensively. PRIMSA protocol includes four stages: (1) identification, (2) screening, (3) eligibility, and (4) inclusion. Figure 1 shows the process of articles selections. We initiated our systematic review by searching for relevant journal and conference articles in several well-known online databases and publishers including Web of Science, IEEE Xplore, ACM, Scopus, SpringerLink, Wiley, and Google Scholar. We used the terms "learning analytics" and "self-regulated", "learning analytics" and "self-regulation", "learning analytics" and "SRL". The search was limited to articles published from 2015 to 2022 (until July 2022). This particular period was selected to ensure that our review focuses on the most recent research in the rapidly evolving field of learning analytics. Prior to 2015, as indicated by studies (Araka et al., 2020) and (Viberg

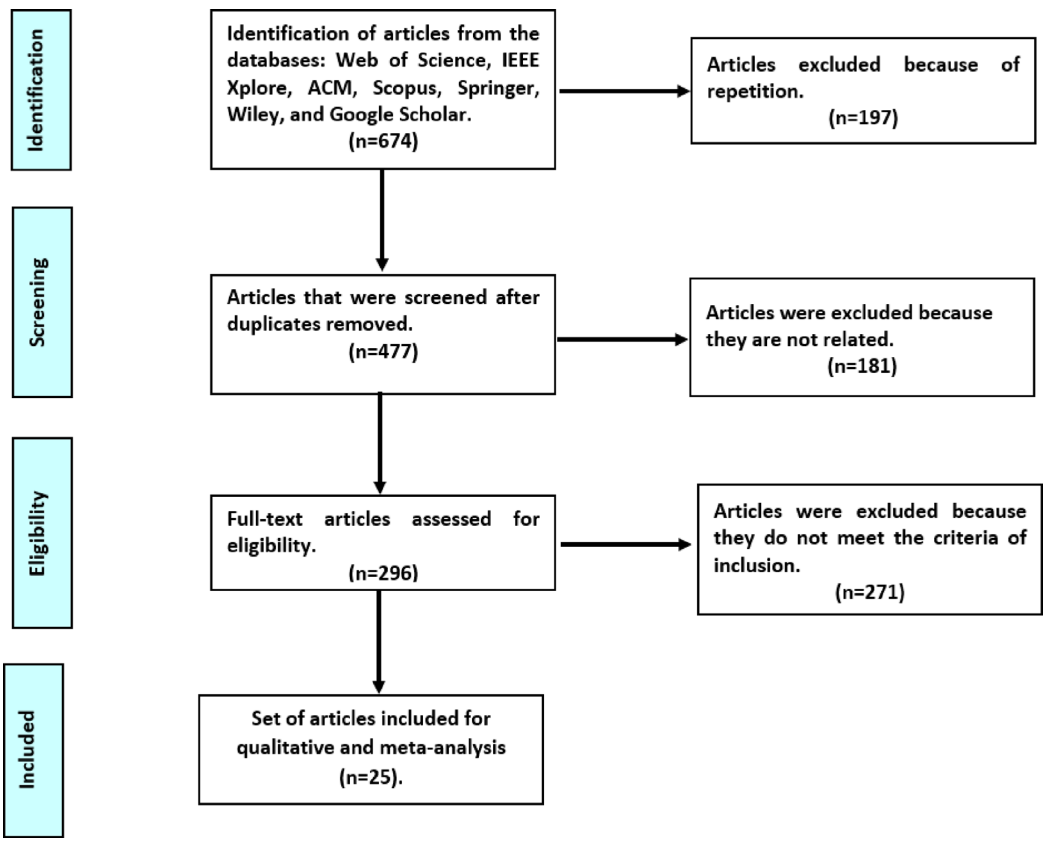

FIGURE 1 PRISMA flow diagram of literature review process used in this study.

et al., 2020), there were few research papers addressing SRL and learning analytics together. However, these early works predominantly focused on exploratory aspects rather than on the practical application of using learning analytics for measuring SRL.

The initial search yielded a total of 674 articles. Duplicated articles were then removed, resulting in 477 articles. Subsequently, a screening process was conducted, involving examining the title, abstract and keyword of each article. As a result of that, 181 papers were excluded as they were not relevant to the topic, some of them included the search terms in their references. They appeared in the search results because they simply included the search terms, for example, many of these papers only include these terms in some of the references. This procedure resulted in 296 articles. In the eligibility stage, we applied the following inclusion criteria: (1) the article should report an empirical study to measure SRL with a clear methodology and results, thus excluding literature reviews, conceptual and theoretical papers. (2) The article should report an empirical study within formal courses in higher education, therefore excluding studies related to schools and informal online courses. (3) The empirical article should be relevant to learning analytics indicators that are extracted from students' trace data and collected automatically through LMS systems. Accordingly, the studies that used other technologies to capture students' behaviours or require learners to input data about their study behaviours were excluded.

To maintain the integrity of the results, every paper underwent a separate evaluation by two authors. They assessed each criterion, where the paper is assessed as "Yes" if it met the criterion and "No" if it did not. In case of disagreement, a third author reviewed the paper, the criterion was then determined by the majority vote among the three reviewers. Only those articles that received a "Yes" for all three criteria from the majority of reviewers were included. After eliminating the articles that did not fulfil the above criteria, 25 articles were selected for critical review to answer the research questions above.

4 | RESULTS

This section presents the findings of our review and the answers to the present study's research questions.

4.1 | Statistical analysis

Table 1 illustrates the details of the included papers. Most of these studies were published in 2022 ($n = 6$), followed by 4 publications in 2021, 2020, 2018, and 2017, respectively, and 3 publications in 2019. In terms of learning settings, the collected studies were implemented in three different learning environments: online, blended, and flipped classroom. The majority of the studies are based on fully online learning ($n = 11$), and blended settings ($n = 10$); few studies were implemented in flipped classrooms ($n = 3$) and only one study was implemented in both two settings: blended and online.

Moreover, the number of students in each study varies between 25 and 8019. The studies included in the present research were carried out in diverse subjects including medical field, psychology, computer engineering and technology, education skills, science, and marketing. The majority of the studies were implemented in a single course, and only few studies involved multiple courses. study (Saqr et al., 2019) involved four courses from the second year of the college of dentistry; the study (Iraj et al., 2021) involved two courses: bioscience and marketing, and study (Cao et al., 2022) involves multiple courses from different departments including science, literature, and art.

4.2 | Research questions analyses

Each study in the collected papers was thoroughly analysed to answer the proposed research questions in this review. For each paper, we collected the indicators that were extracted from students' trace data to measure SRL and examined how each paper validates the results of the proposed measurements. The subsections below highlight the answers for the research questions in detail.

4.2.1 | What are the indicators in trace data that have been used to measure SRL?

Table 2 illustrates the extracted indicators that were used in each of the reviewed studies to measure SRL. The number of indicators employed in these studies varies from one to twelve indicators. These indicators can be categorized into eight types:

1. Engagement indicators: In the context of education, the engagement refers to the degree to which students are involved, committed, and invested in their learning process. Martin and Borup (Martin & Borup, 2022) defines online learner engagement as "the productive cognitive, affective, and behavioural energy that a learner exerts interacting with others and learning materials and/or through learning activities and experiences in online learning environments." This definition identifies three dimension of engagement: cognitive, emotional, and behavioural. These dimensions demonstrate significant interplay; for example, emotional engagement influences cognitive and behavioural engagement. As described in (Martin & Borup, 2022), the behavioural engagement "is the physical representation of cognitive and affective engagement." It can be operationalized through observable online indicators. The studies utilized various indicators to capture the level of learner's engagement in online learning activities. Table 2 illustrates these indicators, which including: overall time a learner spent online accessing learning materials, total number of logins, total number of participations in discussion forums, total number of accessing educational resources in general, total number of watching educational videos, total number of submitting formative

TABLE 1 Collected studies.

Study	Year	Setting	Number of students	Course
(Pardo et al., 2017)	2017	Blended	145	Introduction to computer systems
(Lu et al., 2017)	2017	Online	48	Introduction to computer science
(Yamada et al., 2017)	2017	Blended	127	Information technology
(Saqr et al., 2017)	2017	Blended	133	Man and environment (medical program)
(Li et al., 2018)	2018	Online	2454	Computer-assisted language learning
(Cicchinelli et al., 2018)	2018	Blended	160	Computer science" and "Software development and business management"
(Ilves et al., 2018)	2018	Online	442	Introductory programming course
(Kim et al., 2018)	2018	Online	284	Business statistics course
(Saqr et al., 2019)	2019	Blended	138	Four courses from the second year of College of dentistry
(Montgomery et al., 2019)	2019	Flipped Classroom	157	Education program
(Jovanovic et al., 2019)	2019	Flipped Classroom	2014—(290), 2015—(371), 2016—(486)	First-year engineering course (subject name is not mentioned)
(Tan et al., 2020)	2020	Blended	143	Psychology
(Papamitsiou & Economides, 2021)	2020	Online	122	Management information systems
(Li et al., 2020)	2020	Online	238	Chemistry
(Gadella et al., 2020)	2020	Blended	131	C Programming
(Banihashem et al., 2022)	2021	Online	25	Teaching skills
(Rodriguez et al., 2021)	2021	Online	312	Chemistry course
(Iraj et al., 2021)	2021	Blended +Online	218(blended), 78(online)	Bioscience course (blended), marketing (online)
(Afzaal et al., 2021)	2021	Blended	157	Programming
(Ustun et al., 2022)	2022	Flipped Classroom	31	Introductory computer science course
(Cao et al., 2022)	2022	Blended	8019	Science, literature, and art
(Li et al., 2022)	2022	Online	300	Chemistry course
(Raković et al., 2022)	2022	Blended	340	Biology
(Feldman-Maggor et al., 2022)	2022	Online	954	Chemistry
(Ye & Pennisi, 2022)	2022	Online	65	Agriculture

assessments, total number of viewing course reserves, and total number of days a student accessed online materials.

2. Study regularity indicators: in contrast to the total indicators, regularity indicators involve time dimension when capturing online learner's behaviour. Regularity is a measure of how steadily and consistently a learner accesses online material. It is an indicator of self-regulation and shows learners' consistent commitment to their learning, which indicates they are purposefully planning to study. The reviewed studies employed different ways to calculate and quantify students' access regularity of learning materials. Many studies simply used averages to capture access regularity for online materials. These include the average number of times of accessing learning materials during the whole course (Cicchinelli et al., 2018), the average number of hours and the average number of topics accessed per week (Li et al., 2022), the average number of login per week (Montgomery et al., 2019), and the average number of solving formative assessments per session (Cicchinelli et al., 2018).
3. Other studies used more advanced statistical tools to measure regularity. For instance, the study in (Gadella et al., 2020) used variance of weekly working time on tasks to calculate irregularity instead of regularity. In statistics, variance is used to measure the variability between numbers in a data set. In this context, small number indicates high regularity as it indicates consistent access to online materials. Similarly, studies (Li et al., 2018) and (Kim et al., 2018) used standard deviation to measure irregularity, standard deviation is the square root of the variance. Studies (Jovanovic et al., 2019) and (Cao et al., 2022) used entropy to capture student's regularity of accessing online materials, it is a measure that used to quantify the regularity of fluctuations in time series. In context of student's regularity, entropy measures the unpredictability or complexity of the time series data of a student's access patterns. Higher entropy suggests more unpredictable study patterns, while lower entropy indicates more regular and predictable patterns.

Anti-procrastination indicators: Procrastination refers to the postponement of the initiation or timely completion of a task (Lay, 1986). It is a prevalent phenomenon among college students, where procrastinators delay task completion until they have relatively limited time, resulting in rushed work and lower academic performance.

TABLE 2 Map the extracted indicators to SRL constructs.

Paper	Indictors	Engagement	Regularity	Anti-procrastination	Help-seeking	Monitoring	Planning	Motivation	Environment structuring
(Pardo et al., 2017)	Total number of times a student access educational resource.	√							
	Total number of times a student solves formative assessments.	√				√			
	Total number of times a student accesses the dashboard.	√				√			
(Lu et al., 2017)	Total number of times watching videos.	√							
	Total number of times of participation in forums.	√							
(Yamada et al., 2017)	Total number of pages to read of the learning material per minute.							√	
	Total number of marking and annotation materials through the course.							√	
(Saqr et al., 2017)	Total number of logins.	√							
	Total number of posts replies on forums.	√							
	Total number of hits on course materials.	√							
	Total time spent online	√							
	Total number of attempted formative assessments.	√				√			
(Li et al., 2018)	Total access time.	√							
	Total time of reviewing learning materials.	√							
	The average numbers of days of submitting the quizzes before the deadlines.			√					
	Irregularity of study: standard deviation of accessing online materials over the semester.		√						
	Pacing: total number of quizzes completed before deadlines.			√					
(Cicchinelli et al., 2018)	Total number of access to course organization resources like course dates, assessment deadlines.						√		
	Total number of access to exercises pages.	√				√			
	Total number of solved quizzes.	√				√			
	Total number of solved embedded questions in the contents pages.	√				√			
	Total number of access to content pages.	√					√		
	Average of access to course organization resources		√						
	Average number of access to indices per session.		√						
	Average number of access to exercises pages per session.		√						
	Average number of solved quizzes per session.		√						

TABLE 2 (Continued)

Paper	Indictors	Engagement	Regularity	Anti-procrastination	Help-seeking	Monitoring	Planning	Motivation	Environment structuring
	Average number of solved embedded questions per session.		√						
	Average number of access to content pages (average of regularity).		√						
	Average time until a student return online after each class.		√						
(Ilves et al., 2018)	Number of days that a student starts working on the exercises after they released (starting).			√					
	Number of days that a student works on the exercises (schedule).			√					
	The average of number of days from the deadline of submission set of exercises (earliness).			√					
(Kim et al., 2018)	Total time spent on learning materials (online lectures each week)	√							
	Total number of online lectures visits per week.				√				
	Standard deviation of logins each week.		√						
	Standard deviation of online lecture visits.		√		√				
	Total time spent on the Q&A board each week.		√						
	Total number of visits to the Q&A board per week.				√				
	Total number of messages, replies, questions posted on the Q&A board.				√				
(Saqr et al., 2019)	Total number of interactions in online discussion in the first day of the week.			√					
	Total number of interactions in online discussion in the first three months.			√					
	Total number of interactions per day.		√						
	Total time spent on the course.	√							
	Average number of interactions per day.		√						
(Montgomery et al., 2019)	Location: on-campus versus off-campus								√
	Day of the week.								√
	Time of the day: morning, afternoon, evening, and other.								√
	Total number of logins.	√							
	Total number of viewing learning modules.	√							
	The average number of logins per week.		√						
	Total number of times a student reviewed quizzes online within 24 h before exams.			√					

(Continues)

TABLE 2 (Continued)

Paper	Indictors	Engagement	Regularity	Anti-procrastination	Help-seeking	Monitoring	Planning	Motivation	Environment structuring
(Jovanovic et al., 2019)	Entropy of the number of weekly sessions.		√						
	Entropy of the number of weekday sessions (the variability of study sessions per weekday).		√						
	Entropy of the number of weekly active days.		√						
(Tan et al., 2020)	Total time spent to complete the quizzes.							√	
	Total Number of attempts for quizzes per week.							√	
(Papamitsiou & Economides, 2021)	The average time the student spends on viewing the analytics visualizations					√			
	Total number of times the student accesses analytics visualizations.					√			
(Li et al., 2020)	The average proportions of units studied before the deadline.		√	√					
	The average time of studying units before the deadlines.		√	√					
	The average value of standard deviations of studying units before the deadlines.		√						
	The slope of linear regression that regressed time spent on the system.		√						
(Gadella et al., 2020)	Total Time spent on tasks.	√							
	Variance of normalized weekly working time on tasks (regularity).		√						
(Banihashem et al., 2022)	Total number of posts in discussion forum.	√							
	Total number of logins.	√							
	Total number of watching videos.	√							
	Total time spent on the course materials.	√							
(Rodriguez et al., 2021)	Proportion of videos watched before deadline.			√					
	Proportion of videos watched on due date.			√					
(Iraj et al., 2021)	Total clicks on links sent to the students as feedback.					√			
(Afzaal et al., 2021)	Total number of video views, material views and discussion forum views per course.	√							
	Total number of attempt to solve quizzes.	√				√			
	Total time spent on solving quizzes.	√				√			
(Ustun et al., 2022)	Total number of logins.	√							
	Total number of viewing the course materials.	√							
	Total number of posts on discussion forum in a week	√							
	Total number of optional assessments solved	√							
	Total time spent in a course.	√							

TABLE 2 (Continued)

Paper	Indictors	Engagement	Regularity	Anti-procrastination	Help-seeking	Monitoring	Planning	Motivation	Environment structuring
(Cao et al., 2022)	Total number of days a student access online materials.	√							
	Total time of students being online.	√							
	Regularity: entropy of the time series that captures students' access time.	√							
(Li et al., 2022)	The average number of hours per week the student spend on online materials.		√						
	The average number of topics attempted per week.		√						
(Raković et al., 2022)	Total number of viewing calendar events, announcements, syllabus, and assignment instructions.						√		
	Total number of viewing course reserves.	√							
	Total number of viewing recorded sessions, viewing lectures' slides, download previous exams.	√							
	Total number of submitting (assessments, correct/incorrect answers, self-reflection, exams).	√							
	Total number of: posting questions in the discussion forum, and requesting office hours slots.	√				√			
	Total number of review results of submitted assessments, and view grades.				√	√			
(Feldman-Maggor et al., 2022)	Total number of new videos that a student opened until a specific week.	√							
	The submission status of the first optional assignment (binary value).			√		√			
(Ye & Pennisi, 2022)	Total time spent on reviewing the syllabus and rubrics.						√		
	Total number of visiting items, topics per module	√							
	Average time spent on each module.								
	Total number of participation in forums.	√							
	Average number of late submissions.			√					
	Average number of submissions before deadline.			√					
	Total number of questions asked to the instructor.				√				
	Completion rate of submitting optional self-assessments and bonus quiz.	√				√			
	Average number of retaking quizzes.					√			

Procrastination is associated with poor time management and lack of self-regulation skills. The collected studies used different indicators to measure procrastination or anti- procrastination based on the deadlines of submitting assessments, or finishing studying specific units. The study in (Li et al., 2018) used two indicators to measure anti-procrastination: the average number of days between the deadlines and the day of submitting the quizzes, and the number of quizzes completed before deadlines. The study in (Ye & Pennisi, 2022) used the number of late submission as an indicator of procrastination, while the study in (Ilves et al., 2018) captures anti-procrastination from two angles using two indicators: the number of days that a student started working on the tasks after they were released, and the average number of days of submission before the deadlines. The studies in (Li et al., 2020) (Papamitsiou & Economides, 2021) (Rodriguez et al., 2021) (Feldman-Maggor et al., 2022) measured anti-procrastination based on the proportion of materials studied or tasks completed before the deadlines. Instead of studying procrastination per task (micro level), the study in (Saqr et al., 2019) investigates that on the course level (macro level). It is found that early bird participation can be used as indicator of anti-procrastination, where the study reports that the number of interaction in the first three months was a strong and reliable predictor of students' performance. The term "early birds" typically refers to individuals who start their tasks, activities, or engagements earlier than others do. In the context of online learning activities, the early bird demonstrates self-regulated learning behaviours. It indicates that such learners are likely planning their time effectively, and taking initiative. They are not just avoiding the stress and negative consequences of last-minute work; they are also potentially engaging more deeply with the material, which can lead to better understanding and retention.

4. Help-seeking indicators: Help seeking is an important self-regulated strategy for effective learning. It refers to learners' active role in monitoring their performance and seeking assistance when facing academic obstacles (Karabenick & Gonida, 2017). Only few studies measured this skill based on students' participation in discussion forums. For instance, the study in (Kim et al., 2018) measures help-seeking using three indicators: the total time spent on Q&A board, the number of visits, and the number of participation in Q&A board, while the study in (Raković et al., 2022) used two indicators: the number of posting questions in the discussion forums and requesting time slot during office hours. Ye and Pennisi (Ye & Pennisi, 2022) used the total number of questions asked to the instructor as an indicator of help-seeking.
5. Monitoring Indicators: Self-monitoring is another important component of SRL and is related to the concept of self-assessment. It helps learners become aware of their progress and make necessary adjustments to achieve their goals. Different approaches were used to capture this skill based on indicators that represent students' behaviours to monitor and get feedback about their performance. The studies in (Pardo et al., 2017) and (Papamitsiou & Economides, 2021) used the number of times students accessed to dashboard analytics visualizations as an indicator of students' self-monitoring behaviour. Dashboards are tools that visualize learners' trace data and performance in order to improve their self-awareness of their learning. The study in (Pardo et al., 2017) used only the total number of times accessing the dashboard, whereas the study in (Papamitsiou & Economides, 2021) used the total number of times and the average time students spent viewing the dashboard. Another approach was used by the study in (Iraj et al., 2021) where the study aimed to capture students access to the feedback sent to them by embedding links in the feedback messages. Moreover, solving formative assessments can be viewed a self-evaluation behaviour, indicating students' awareness of their learning progress. The studies (Cicchinelli et al., 2018) (Pardo et al., 2017) (Saqr et al., 2017) (Afzaal et al., 2021) (Ustun et al., 2022) (Raković et al., 2022) (Feldman-Maggor et al., 2022) (Ye & Pennisi, 2022) used the total number of formative assessment submissions as an indicator of monitoring. Additionally, the study in (Raković et al., 2022) considered the total number of viewing the grades of submitted assessments an indicator of monitoring.
6. Planning indicators: Planning, on the task level, entails setting sub goals before engaging in the task (Winne, 1997). Self-regulated students used to set their learning goals at the beginning of the tasks, so accessing any online materials that guide students to achieve these tasks can be considered indicators of planning behaviour. The study in (Cicchinelli et al., 2018) captures this skill using the total and average number of access to course organization resources such as contents objectives, and assessments deadlines. Similarly, the studies (Raković et al., 2022) and (Ye & Pennisi, 2022) measure this component using total number of access to syllabi, rubrics, calendar, and assessments' instructions.
7. Motivation indicators: Measuring motivation is a complex and challenging task. Only studies in (Yamada et al., 2017) and (Tan et al., 2020) aimed to measure this construct indirectly through learning behaviours. The study in (Tan et al., 2020) measures learner's motivation using quiz completion time as an indicator of motivation. The study found that motivated students engaged in retrieval practice during low-stakes quizzes, which involves recalling answers from memory rather than looking them up in the textbooks. As a result, they took less time to complete the quizzes. Retrieval practice is promoted by learners' motivation to increase the attention they dedicate to tasks. Similarly, the study in (Yamada et al., 2017) used the total number of pages to read online materials per minute and total number of marking annotation as indicators for intrinsic motivation. These behaviours were associated with learners' awareness of cognitive strategies, which were motivated by intrinsic value.
8. Environment structuring indicators: Environment structuring in SRL refers to a learner's strategies regarding the choice and organization the learning environment to optimize their study experience and minimize distractions. The study in (Montgomery et al., 2019) captures environment structuring using three indicators: location, day-of-the-week, and time-of-the-day. Location is identified as

"On-campus" or "Off-campus" based on the IP address. The day of the week was extracted from the data of online access that includes date and time. The access time of the day was categorized into four periods: "Morning" (5:00 am–11:59 am), "Afternoon" (12:00 pm–5:59 pm), "Evening" (6:00 pm–11:59 pm), and "Other" (12:00 am–4:59 am).

4.2.2 | Research question 2: How have the interpretations of the proposed measurements results been validated?

The validity of an instrument or a protocol used to measure SRL is concerned with whether that approach accurately measures the intended SRL process rather than other phenomena (Fan et al., 2022). Using learning analytics to measure SRL skills involves mapping raw trace data to learning events and then identifying SRL process from these events. As it is illustrated in Table 3, the majority of the collected studies did not explicitly address this issue. Instead, they merely evaluate the validity of the proposed measurement by examining their ability to predict students' performance (predictive validity). This approach can be observed in the studies (Lu et al., 2017), (Saqr et al., 2017), (Li et al., 2018), (Ilves et al., 2018), (Saqr et al., 2019), (Montgomery et al., 2019), (Jovanovic et al., 2019), (Gadella et al., 2020), (Rodriguez et al., 2021), (Iraj et al., 2021), (Afzaal et al., 2021), (Cao et al., 2022), (Li et al., 2022), (Raković et al., 2022), and (Feldman-Maggor et al., 2022). While these studies aim to measure SRL, they did not establish a link between the used indicators and SRL processes. Instead, they assume that academic performance is a consequence of self-regulation, and focused only on evaluation the relation between these indicators and students' performance. Likewise, the study in (Papamitsiou & Economides, 2021) used students' performance in self-assessment, instead of academic performance, to evaluate the predictability of the indicators used. The study in (Pardo et al., 2017) found that combining trace data indicators with data collected using Motivational Strategies for Learning Questionnaire (MSLQ) improved the prediction of students' academic performance. On the other hand, studies (Yamada et al., 2017), (Kim et al., 2018), (Tan et al., 2020), and (Li et al., 2020) used Motivational Strategies for Learning Questionnaire (MSLQ) to map the identified events collected from trace data to SRL process captured by this questionnaire. Similarly, the study in (Ye & Pennisi, 2022) mapped the results to the data collected by Online Self-Regulated Learning Questionnaire (OSLQ). The studies (Banihashem et al., 2022) and (Ustun et al., 2022) involved traditional instruments including Self-regulation Questionnaire, Agent Engagement Scale, and self-regulated learning scale (S-RLS). However, these studies aimed to investigate the impact of the intervention based on learning analytics on the learners' self-regulated skills not to validate the trace-data measurement.

TABLE 3 Tools to validate the LA-based measurements of SRL.

Study	Validation
(Pardo et al., 2017)	• MSLQ • Academic performance.
(Lu et al., 2017)	• Academic performance.
(Yamada et al., 2017)	• The Motivated Strategies and Learning Questionnaire (MSLQ) • Academic performance
(Saqr et al., 2017)	• Academic performance.
(Li et al., 2018)	• Academic performance
(Cicchinelli et al., 2018)	• Motivational Beliefs and Self-Regulation Strategies (MBSRS) questionnaire.
(Ilves et al., 2018)	• Academic performance.
(Kim et al., 2018)	• Motivation for SRL Questionnaire (MSLQ)
(Saqr et al., 2019)	• Academic performance
(Montgomery et al., 2019)	• Academic performance
(Jovanovic et al., 2019)	• Academic performance
(Tan et al., 2020)	• Need for Cognition Questionnaire (NFC). • Self-efficacy, critical thinking, and effort regulation scales from Motivated Strategies for Learning Questionnaire (MSLQ). • Achievement goal questionnaire. • Exam performance.
(Papamitsiou & Economides, 2021)	• The self-assessment score
(Li et al., 2020)	• MSLQ • Academic performance
(Gadella et al., 2020)	• Academic performance
(Banihashem et al., 2022)	• Self-Regulation Questionnaire • Agent Engagement Scale
(Rodriguez et al., 2021)	• Academic performance
(Iraj et al., 2021)	• Academic performance
(Afzaal et al., 2021)	• Scores of quizzes.
(Ustun et al., 2022)	• Self-regulated learning scale (S-RLS) Questionnaire • Student opinion form (specifically developed for this study) • Academic performance
(Cao et al., 2022)	• Academic performance
(Li et al., 2022)	• Academic performance
(Raković et al., 2022)	• Students' performance in exam 1 and exam 2.
(Feldman-Maggor et al., 2022)	• Student's success
(Ye & Pennisi, 2022)	• Online Self-Regulated Learning Questionnaire (OSLQ) • Academic performance

5 | DISCUSSION

This paper aims to examine how previous studies have used online trace data to measure students' SRL. These studies extracted students' learning behaviour from a single course. However, it is important to note that data extracted from a specific course maybe influenced by the course context, and students behaviour might differ in other courses due to varying interests and different course demands (Ye & Pennisi, 2022). The included studies employed a range of indicators to capture learners' self-regulation, with many of them are related to time management skills. These include indicators related to engagement, regularity, and anti-procrastination. Therefore, the indicators used for these SRL processes might overlap. Our study finds that the majority of these studies did not validate the proposed measurements based on theoretical models.

5.1 | Self-regulation indicators

The collected studies in this review have used various indicators to measure different SRL processes. The number of indicators utilized in each paper varies as well as the number of SRL constructs. Table 4 summarizes the number of papers that measure each one of SRL constructs.

Most of the papers focused on indicators that capture students' engagement. Many of these studies used total indictors as a measure of engagement of students' efforts with online educational materials. The purpose of these indicators is to quantify learner's cognitive engagement in the subject. These include the total of login times, the total of hits, the total of messages posted in a forum, and the overall of time spent online. It is important to note that while engagement and SRL are distinct conceptual frameworks in learning science, they often overlap and intertwine in practice. Engagement is considered an outcome of self-regulation (Wolters & Taylor, 2012). It is noteworthy that this type of indicators provide a broad measure and does not consider time dimension. Therefore, it might not reflect self-regulation precisely, for example, a high number of accesses might indicate a short attention span (Asarta & Schmidt, 2013). Moreover, the high number of accesses might result from cramming behaviour close to exams rather than a frequent regular study over the semester period, which indicates poor time management that does not reflect self-regulation behaviour. Previous research (Asarta & Schmidt, 2013) (You, 2016) found that the quantity of learning behaviours exhibited a weak correlation with course achievement. It was also found that the total amount of time invested in online learning did not vary greatly between self-regulated and non-self-regulated learners (Kim et al., 2018) (Gadella et al., 2020). Therefore, further research is needed to identify different types of engagement and use different indicators to accurately measure this process.

TABLE 4 Number of papers that measure each SRL construct.

SRL construct	Number of papers
Engagement	16
Regularity	9
Anti-procrastination	8
Help-seeking	3
Monitoring	8
Planning	3
Motivation	2
Environment structuring	1

On the other hand, regularity represents a strong predictor of students' performance (Jovanovic et al., 2019) (You, 2016). The collected studies used varies statistical approaches to quantify learners' regularity of accessing online learning materials including average, variance, standard deviation, and entropy. Using the average number of accesses alone as an indicator of regularity does not capture the distribution of access over the period of time. For example, if a learner did not access the online materials for many weeks, and then accessed them more frequently within a week, possibly close to the exams and deadlines, the average number of access maybe the same as other learners who accessed on a weekly basis but with fewer number of times each week.

Variance, standard deviation, and entropy are indicators of irregularity, so small values indicate more regular access to online materials. However, these indicators assume constant learner behaviours and cannot capture learner adaptation behaviour, which is an essential process in SRL theories. Students with SRL skills are supposed to adapt their learning strategies and behaviours, when they find that their current approaches are not effective in achieving their goals. This adaptation includes changes in their pattern of accessing online educational materials. Therefore, it is necessary to consider other indicators that capture adaptation when measuring regularity. This involves measuring behaviour changes in relation to learners' performance in summative and formative assessments.

It is noteworthy that regularity is related to anti-procrastination, both of them are time management skills. Therefore, it is expected that students with high SRL skills will access online materials consistently for studying and submit learning tasks ahead deadlines. However, it is important to note that regularity and anti-procrastination measure different aspects of SRL process. Regularity indicates the commitment to consistent access to the materials, while anti-procrastination indicates timely task initiation behaviour. Yet, there is no research that investigates the relationships between these two types of indicators.

Only a few of the collected studies focused on measuring help-seeking process, most of them used indicators based on discussion forums. This represents a challenge because online discussion forums usually have low level of engagement. Moreover, the level of engagement might be impacted by a variety of factors like learner's relationship with the instructors or with peers, the nature of the subject, and the learning setting, whether it is fully online, or blended learning.

Generally, relying exclusively on students' data that was extracted from a single course provides an incomplete insight into students' learning behaviours. Typically, students are enrolled multiple courses per semester, each with its own workload and challenges. The amount of time and effort dedicated to each course can vary based on their priorities, deadlines, and perceived importance. This can result in variations in their engagement and participation within a specific course, which might not be apparent when considering only the data from that course. Therefore, to gain a more complete insight into students' learning behaviours and measure their SRL, a holistic view of students' academic experiences should be captured through analysing data from all courses in which students are enrolled during the semester.

Additionally, student's online behaviour is significantly influenced by course's instructional design. Courses that are rich in online educational materials and learning activities typically foster greater interaction, while those with fewer resources and activities tend to result in less student engagement.

5.2 | Validity of the measurements

In the field of education, validity is defined by Messick as the "degree to which empirical evidence and theoretical rationale supports the adequacy and appropriateness of inferences and actions based on test scores" (Messick, 1989). Messick's framework expanded the concept of validity to include not just the test (construct validity) but also the consequences and interpretations of its results (consequential validity), making it a comprehensive approach to understanding and evaluating the effectiveness of a measurement tool.

When it comes to trace-based measurement, validity is bound to what these indicators represent (theoretical foundation) (Winne, 2020). Despite the majority of the collected studies used learners' performance as evidence, they did not establish a clear mapping between the indicators and specific SRL processes. Instead, they only assess the correlation between the calculated indicators and learners' performance (consequential validity). Fundamentally, it is often challenging to bind specific indicators to SRL processes because an indicator can represent different process, for example accessing the syllabus could be interpreted as Planning as well as Monitoring.

Alternatively, the validity of trace-based measurements can be improved by triangulate them with other instruments that measure the same events, for example studies (Yamada et al., 2017), (Kim et al., 2018), (Tan et al., 2020), and (Li et al., 2020) used MSLQ self-report to support the validity of the proposed indicators and measurements. However, this approach may introduce a challenge in the form of divergence between these measurements due to the inherent disparities in their natures. Self-report questionnaires tend to capture SRL as a stable aptitude belonging to an individual indicating how an individual usually studies across different contexts and tasks. Conversely, trace-based measurement captures actual learner's behaviours as performed events rather than mental states that generate such actions (Fan et al., 2022). These actions might vary across different subjects or even within the same subject when confronted with different tasks. For example, students might employ different learning strategies when studying mathematics compared to studying humanities subjects. Additionally, learners are likely to exhibit different behaviours when preparing for an exam compared to working on a class assignment (Rovers et al., 2019). Therefore, in order to enhance the validity of trace-based measurement, it is valuable to trace learners' behaviours across different subjects and semesters. This approach allows for a more comprehensive understanding of student learning behaviours, considering the variations that arise across different contexts and tasks as well as the adaptations in these behaviours. By examining these behaviours in multiple settings and points of time, researchers can address the limitations associated with relying solely on self-report questionnaires and derive deeper insights into SRL processes.

6 | LIMITATION AND FUTURE RESEARCH

In our paper, we used the terms "learning analytics" and "self-regulated", "learning analytics" and "self-regulation", "learning analytics" and "SRL" to search for related papers. The keywords were selected based on their prevalent use in existing literature and their direct relevance to the core concepts being investigated. Our objective was to ensure a focused and relevant collection of data while aligning with the standard terminologies and concepts recognized in the field. However, this may have excluded studies that used different keywords or terminologies not captured by our initial criteria. For example, research that uses keywords like "trace data", "click-stream data", which, while relevant, were not included.

Another limitation of this paper is its exclusive focus on studies that measure Self-Regulated Learning (SRL) utilizing trace data obtained from Learning Management Systems (LMS). This approach was selected due to the prevalent and accessible nature of LMS data in higher education and educational research in general. These exclude studies that capture learner's behaviours using other methods. Future research could include studies that used other channels, multimodal learning analytics (MMLA), like eye-tracking sensors, camera, wearable and bio-physical sensors to collect data about learners' behaviours as well as to detect their cognitive and metacognitive strategies that represent the core of SRL processes.

7 | CONCLUSION

This study reviewed 25 empirical studies that utilized trace data to measure learners' SRL skills. Various indicators have been extracted from learners' trace data to capture SRL skills, with a particular focus on time management attributes like engagement, regularity, and anti-procrastination. Some of these indicators fall short in effectively representing the complexities inherent in SRL. For example, total login times might reflect mere presence rather than active engagement, offering little insight into the quality or intensity of learning. Hits or page views can inflate perceived interaction, not distinguishing between purposeful navigation and aimless browsing. Similarly, total time spent online is a simplistic measure that assumes more time equates to better learning, disregarding the efficiency or effectiveness of that time.

We identified that most studies concentrated on single-course data extracted from LMS, which may not fully encapsulate the multi-dimensional and context-sensitive nature of SRL. Furthermore, while a range of indicators has been employed to capture different SRL constructs, the overlap between these indicators and the lack of validation against theoretical models raise concerns about the precision and applicability of the findings.

As the field of learning analytics continues to evolve, it is imperative to fill the gap between data-driven insights and learning science. This requires a closer collaboration between researchers and practitioners from both domains to ensure that the metrics and methods developed are not only theoretically sound but also practically relevant. By addressing these challenges, the field can move toward a more holistic and accurate understanding of SRL, ultimately contributing to the design of better learning experiences and outcomes.

AUTHOR CONTRIBUTIONS

Saleh Alhazbi: Conceptualization; investigation; funding acquisition; writing – original draft; methodology; writing – review and editing; project administration; supervision. **Afnan Al-ali:** Investigation; writing – review and editing; formal analysis; writing – original draft; data curation; visualization. **Aliya Tabassum:** Investigation; formal analysis; writing – original draft; data curation. **Abdulla Al-Ali:** Writing – original draft; conceptualization. **Ahmed Al-Emadi:** Conceptualization; writing – original draft. **Tamer Khattab:** Conceptualization; writing – original draft. **Mahmood A. Hasan:** Conceptualization; writing – original draft.

ACKNOWLEDGEMENTS

This work was made possible by grant number RRC02-0731-210013 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors. Qatar University Open Access publishing facilitated by the Qatar National Library, as part of the Wiley - Qatar National Library agreement.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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How to cite this article: Alhazbi, S., Al-ali, A., Tabassum, A., Al-Ali, A., Al-Emadi, A., Khattab, T., & Hasan, M. A. (2024). Using learning analytics to measure self-regulated learning: A systematic review of empirical studies in higher education. *Journal of Computer Assisted Learning*, *40*(4), 1658–1674. https://doi.org/10.1111/jcal.12982