The Use of Self-Regulation of Learning in Recommender Systems: State-of-the-Art and Research Opportunities

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Keywords: Online Education, Self-Regulated Learning, Virtual Learning Environment.

Abstract: Self-regulated learning is defined as the degree to which students are metacognitive, motivationally, and behaviorally active participants in their learning. Learning can be influenced and improved to achieve successful academic results. This article reviews the literature to analyze and compare learning self-regulation strategies to recommend learning objects in the context of a Virtual Learning Environment. The results serve to map the state of the art, main approaches, and characterizations of the topic of recommendation systems that use self-regulated learning strategies to support students' academic performance; and to identify promising opportunities for future research on the topic.

1 INTRODUCTION

Online education has brought new education opportunities, but it has also brought many challenges for students, such as deciding what, when, how, and for how long to learn (Cerezo et al., 2020). When students learn in an online environment, they can hardly regulate their learning, thus failing to achieve objectives (Hidayah et al., 2018). It is necessary to support them to have autonomy in their learning (Pierrot et al., 2021), and several studies have been proposed to help them plan tasks and monitor their performance (Afzaal et al., 2021).

Previous studies have shown that a lack of self-regulated learning (SRL) skills can be a major factor leading to failure of students and dropout from courses (Afzaal et al., 2021). In this sense, for online learning to be successful, students need to possess these SRL skills (Wang et al., 2021). Self-regulated students are aware of their learning process and can take an active role in adapting to different learning environments (Leite et al., 2022). Given this, it is essential to investigate which SRL strategies are most effective, and which can be recommended, aiming to help students improve their academic performance.

The purpose of this study is to analyze and compare strategies on the topic of SRL strategies for recommending learning objects in Recommendation Systems (RS), in the context of a Virtual Learning Environment (VLE). In turn, analysis and comparison allow one to glimpse the state-of-the-art and identify research opportunities on the topic. For that, the article addresses five research questions (RQs) as presented in Table 1. RQ1 to RQ5 are answered by works on the topic that have been reported in the recent literature and the answer to RQ6 is extracted from the answers to RQ1-5. The study is carried out using a systematic literature review spanning back over 5 years (from 2018 to mid-2023).

The main contributions of this study are (i) an updated analysis of recent works on the topic that can serve as support for guiding educators, IT professionals, and researchers interested in understanding, building, or applying SLR-based RS to VLEs; (ii) the provision of a synthesized body of knowledge for future reference and research.

The remainder of the article is divided into 5 sections. Section 2 provides a brief overview of the con-

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Neo, A., Moura, J., Régis de Araújo, J., Neo, G. and Freitas Júnior, O.
The Use of Self-Regulation of Learning in Recommender Systems: State-of-the-Art and Research Opportunities.
DOI: 10.5220/0012619400003693

In *Proceedings of the 16th International Conference on Computer Supported Education (CSEDU 2024) - Volume 2*, pages 525-532
ISBN: 978-989-758-697-2; ISSN: 2184-5026

Table 1: Research Questions for the Systematic Review on the Topic of Learning Self-Regulation in RS for VLE.

ID	Research questions
RQ1	What is the impact of student self-regulation and interaction dynamics on recommendation in VLEs?
RQ2	Which SRL strategies are carried out by students in a VLE?
RQ3	How does a student's current posture influence their ability to self-regulate their learning in a VLE?
RQ4	How to measure SRL?
RQ5	Which datasets are used in the research?
RQ6	Which are promising opportunities for further research on the topic?

cepts of VLEs, RS, and SRL to facilitate the reading of the following sections. Next, Section 3 will present the methodology adopted in the research. Section 4 analyzes the findings regarding RQ1-5. Section 5 explores the research gaps in the findings (RQ6). The said gaps, if narrowed, could further enhance the topic and cover its applications more comprehensively. Section 6 brings final considerations.

2 THEORETICAL FOUNDATION

2.1 Virtual Learning Environment

The Virtual Learning Environment (VLE) is a technological educational resource in which the learning process depends entirely on the use of a computerized environment and/or online resources (Al-Obaydi, 2020). In VLE, students carry out educational activities, answer questionnaires, watch video classes, and study reading materials (Al-Obaydi, 2020).

Technological educational resources, such as VLE, can be a positive factor in the development of SRL processes, enabling students to focus more on the proposed activities (Lima and Silva, 2010). Various VLEs have emerged over time to support SRL by offering personalized instructions or feedback to students without teacher intervention (Wang et al., 2022). Some studies developed VLEs complemented with metacognitive supports, allowing students to implement important metacognitive strategies and demonstrated learning gains for students who used the VLE (Hidayah et al., 2018; Odilinye and Popowich, 2020).

Recommendations in a VLE provide additional benefits to students who follow them, improving their motivation and performance (Takami et al., 2022). The recommendation can be more useful because it can use the students' actions and interactions, gestures and mouse clicks, learning patterns and processes, reflecting students' cognitive and metacognitive events captured in VLEs (Cerezo et al., 2020).

2.2 Recommendation Systems

Recommender systems (RS) have gained popularity in the educational field, offering different types of recommendations for students, teachers, and schools; identifying interesting learning materials from a large set of resources, and reducing information overload by recommending the right content at the right time and in the right format for the learner (Odilinye and Popowich, 2020). These recommendations are important for the learning process, allowing teachers and students to find content appropriately, according to their profile and needs (Brito et al., 2014; Dwivedi and Roshni, 2017; Obeid et al., 2018).

Some RS are designed to support SRL by providing recommendations on demand or automatically when certain conditions are met (Odilinye and Popowich, 2020). For a self-regulated RS, personalization of recommendations through student modeling is necessary (Hidayah et al., 2018). Personalized learning recommendations are necessary to meet each student's specific learning needs and preferences and improve the learning experience. Each learner has individual needs and specific requirements, and the learner model is used to capture information about learner characteristics such as learning objectives, learning style, prior knowledge, and more (Odilinye and Popowich, 2020).

2.3 Self-Regulation of Learning

Self-Regulation of Learning (SRL) is defined as the degree to which students are metacognitive participants (students' ability to establish plans, schedules, or goals to monitor or evaluate their learning progress), motivational (students who are self-motivated and willing to take responsibility for their successes or failures), and behaviorally active in their learning. For learning to be effective, students need to intentionally activate, sustain, and adjust their cognition, affect, and behavior to achieve their learning goals (Kuo et al., 2014; Wang et al., 2021).

A self-regulated learner is a student who approaches educational tasks with confidence, diligence, and resourcefulness. Therefore, self-regulated students can evaluate their learning strategies and choose their skills and areas of weakness, as they can modify their learning strategies to achieve the desired academic result (McLellan and Jackson, 2017; Wang et al., 2022).

Choosing and monitoring learning strategies are key factors in the student's learning process (Hidayah et al., 2018). Proposals for SRL include models that consider the regulation of affect, behavior, and cognition, recognizing the importance of emotional management (Boruchovitch, 2014; Ben-Eliyahu and Linnenbrink-Garcia, 2015). Studies indicate that students' academic performance depends on several factors, including self-regulation processes that contribute to motivation and academic learning (Ben-Eliyahu and Linnenbrink-Garcia, 2015; Soares, 2018).

There are some ways to measure SRL, Pintrich et al. (1991) developed the MSLQ metric scale - Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991; Polydoro and Azzi, 2009). MSLQ uses 81 items to assess students' motivational orientation and learning strategies in a specific course or discipline. Another way is the EAREL scale (Online Learning Self-Regulation Scale), which focuses on SRL strategies for distance learning activities, to measure students' self-regulation skills (Pierrot et al., 2021).

3 METHODOLOGY

In this article, we carry out a secondary study to identify, analyze, and interpret information related to the research questions. We used the following activities: planning, conducting, and reporting results (Keele et al., 2007). First, a protocol for the review was designed, which involves defining the research questions and filtering the results based on previously defined criteria, in addition to removing duplicate articles and the search term used. To assist in this process, the tool parsing.al[1] was used to record the steps used.

Search Terms: Based on the requirements, the search term was proposed with the help of the Population, Intervention, Comparison, Result, and Context (PICOC) structure. PICOC is used to formulate research questions in systematic searches, as it covers all the elements necessary to construct questions focusing on the real objective (Babar and Zhang, 2009). We present in Table 2 the PICOC for this Systematic Literature Review.

In total, three keywords in the English language were used as search terms. First, keywords related to self-regulation of learning ("self-regulation" OR "self-regulated"). Afterward, keywords related to online education and virtual learning environments ("e-learning" OR "online education" OR "online learning" OR "ITS" OR "MOOC" OR "LMS"). And finally, the keywords related to recommendation

[1] https://parsif.al/

Table 2: PICOC from Systematic Literature Review.

Aspect	Value
Population (P)	SR of learning, SR learning strategies
Intervention (I)	Recommender Systems
Comparison (C)	Other Literature Reviews
Results (O)	Research where SRL is used to improve the academic performance of students in RS.
Context (C)	Online education, virtual learning environments, last 5 years.

systems ("recommendation systems"). The **Search String** used has thus the following logical syntax: ("self-regulation" OR "self-regulated") AND ("e-learning" OR "online education" OR "online learning" OR "ITS" OR "MOOC" OR "LMS") AND ("recommendation systems").

Selection of Articles: The article selection process involved the phases of the PRISMA Statement (Moher et al., 2010) when instantiated to our review, as shown in figure 1. Using the Search String we obtained 272 results in the databases as given in Table 3.

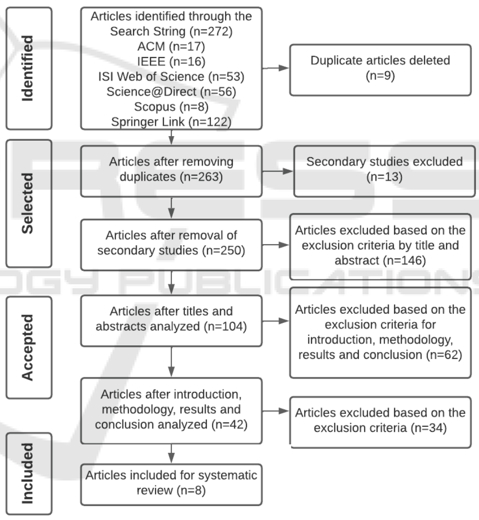

Figure 1: Selection flowchart used in this research based on PRISMA (Moher et al., 2010).

Table 3: Number of Articles Selected by Search String from the listed Databases.

List of Bases	Number of Articles
ACM Digital Library	17
IEEE Digital Library	16
ISI Web of Science	53
ScienceDirect	56
Scopus	8
SpringerLink	122
Total	**272**

Among the 272 selected articles, 13 systematic literature reviews were found. Although several reviews have been carried out to understand the field of personalized learning in recommender systems, only one of them has focused on SRL, exploring its application (Rasheed et al., 2020). In (Rasheed et al., 2020), a systematic review is carried out to identify the challenges in the online component of hybrid teaching from the perspective of students, teachers, and educational institutions. The main challenges students face are related to self-regulation and the use of learning technology.

In the article selection phase, we excluded 9 duplicate articles, 1 article from the IEEE, 2 articles from Web of Science, 5 articles from Scopus, and 1 article from SpringerLink; no articles from the ACM and ScienceDirect were excluded at this stage. Selection criteria were developed to select articles that discuss SRL approaches and strategies in recommender systems in the context of VLEs. According to the research objectives, inclusion and exclusion criteria were adopted, as shown in Table 4.

Based on the inclusion and exclusion criteria, 104 articles were selected by reading the title and summary, then we selected 42 articles based on reading the introduction, methodology, results, and conclusion. We finalized the selection of articles using the inclusion and exclusion criteria and selected 8 articles, 3 articles from IEEE, 1 article from Web of Science, 1 article from ScienceDirect, 1 article from Scopus, and 2 articles from SpringerLink. Articles from the ACM Digital Library were not selected, as they were excluded based on the exclusion criteria.

To respond to the RQs, qualitative research was carried out, which made it possible to obtain descriptive data about students' behavior regarding their way of learning. Qualitative research is important in the educational area, as it is essential to understand human reality, the difficulties experienced and the attitudes and behaviors of the subjects involved, thus constituting essential theoretical support for educational research (Ferreira, 2015). In the data extraction phase, we extract data related to the research context to infer whether a tool was used or proposed and which tool was used or proposed; use of SRL and system dynamics; the impact of students' self-regulation and interaction dynamics on VLE recommendations; the learning self-regulation strategies carried out by VLE students; how SRL was measured and what data sets were used.

4 RESULTS STATE-OF-THE-ART (RQ1-5)

The articles were selected based on the inclusion and exclusion criteria, as well as the quality criteria. We selected 8 articles, 3 articles from the IEEE Digital Library, 1 article from the ISI Web of Science, 1 article from ScienceDirect, 1 article from Scopus, and 2 articles from Springer Link, no article from the ACM Digital Library was selected, as it was excluded based on the exclusion criteria.

The articles selected in this review are presented in Table 5. Taken together, these studies offer a snapshot of the state-of-the-art of the topic of interest here and indicate a positive trend in the use of technologies to promote self-regulation by personalizing the learning experience and providing valuable feedback to students. However, it is important to recognize that implementations must consider the diversity of educational contexts and the needs of individual students.

The articles included in this literature review address the impacts and strategies of SRL on students' academic performance, as well as how self-regulation is measured, and which databases are used. In the following subsections, we provide answers to the research questions 1 to 5.

4.1 RQ1: What Is the Impact of Student Self-Regulation and Interaction Dynamics on Recommendation in VLEs?

The use of SRL strategies has a significant positive impact on students' interaction with the VLE, being one of the main factors for the recommendations received to be as assertive as possible, helping students' academic performance. In (Odilinye and Popowich, 2020) study, student-generated metacognitive strategies, such as highlighting and marking text, were necessary to build a learning model that enabled appropriate personalized recommendations for completing educational tasks. In (Wang et al., 2022), after adapting the existing VLE using the Personalized Quiz Algorithm (PQ) and Knowledge Recommendation Algorithm (KR), adaptively personalized quizzes and recommendations were generated for individual students, supporting students' SRL.

Studies such as those by (Afzaal et al., 2021; Hidayah et al., 2018; Wang et al., 2021) demonstrated that SRL had a positive impact on the student's academic performance in the courses. (Afzaal et al., 2021) contributed by offering automatic, intelligent recommendations developed from algorithms to help students and teachers understand which resources a student should work on to achieve the desired level of performance. (Hidayah et al., 2018) contributed to the generation of objective/sub-objective recommendations, with recommendations for the use of strate-

Table 4: Inclusion and Exclusion Criteria.

Inclusion Criteria	Exclusion Criteria
1. Studies that present some approaches to self-regulation in learning environments. 2. Studies that provide empirical evidence on the advantages of using self-regulation techniques. 3. Studies that focus on using SRL techniques to improve student's learning experience and help teachers and tutors manage their students and groups. 4. Peer-reviewed studies that provide answers to research questions.	1. Duplicate studies. 2. Articles published before 2018. 3. Publications not related to the educational field. 4. Studies that are not related to VLE. 5. Studies not related to recommendation systems. 6. Studies that do not present approaches to SRL. 7. Non-peer-reviewed studies. 8. Secondary studies. 9. Gray literature.

Table 5: Selected Articles.

Article	Authors	Year
Automatic and Intelligent Recommendations to Support Students' Self-Regulation	Afzaal, Nouri, Zia, Papapetrou, Fors, Wu, Li, and Weegar.	2021
Facilitating English Grammar Learning by a Personalized Mobile-Assisted System with a Self-Regulated Learning Mechanism	Wang, Chen and Zhang	2021
Personalized Recommender System Using Learners' Metacognitive Reading Activities	Odilinye and Popowich	2020
Process mining for self-regulated learning assessment in e-learning	Cerezo, Bogarín, Esteban, and Romero.	2020
Promoting self-regulated learning strategies for first-year students through the COMPER service	Pierrot, Michel, Broisin, Guin, Lefevre, and Venant	2021
The relationship between self-regulated student use of a virtual learning environment for algebra and student achievement: An examination of the role of teacher orchestration	Leite, Kuang, Jing, Xing, Cavanaugh, and Huggins-Manley	2022
A Framework for Improving Recommendation in Adaptive Metacognitive Scaffolding	Hidayah, Adji and Setiawan	2018
IFSE - Personalized Quiz Generator and Intelligent Knowledge Recommendation	Wang, Li, Zimmermann, Pinkwart, Werde, Van Rijn, DeWitt, and Baudach	2022

gies that contribute to students' SRL and the improvement of academic performance.

In (Wang et al., 2021), results showed that participants who used SRL strategies significantly outperformed the participants of the control group in test scores. In (Cerezo et al., 2020), the development of alert systems to predict students at risk during a course, and the personalization of self-regulated VLEs, with the construction of RS based on different SRL behaviors, have a positive impact on student academic performance. Consistent evidence from these studies reinforces the conclusion that promoting SRL is important to optimize the learning experience in VLEs, providing more effective recommendations and directly contributing to students' academic success.

4.2 RQ2: Which SRL Strategies Are Carried Out by Students in a VLE?

As the answer to RQ1 indicates, the use of SRL strategies promotes an increase in student academic performance. Students use SRL strategies to evaluate their experience in the course, motivation to complete the course, carry out tasks, analyze the time to complete the task, and analyze the completion and grades obtained in the course (Afzaal et al., 2021). They also carry out strategies related to defining their learning goal, deciding the level of the learning material, choosing between reviewing previously incorrectly answered questions or new questions, and receiving a report with their performance for reflection on learning (Wang et al., 2021).

Students carry out metacognitive reading activity strategies (text marking, tags) to extract the most relevant information from the text (Odilinye and Popowich, 2020), action strategies indicative of understanding and learning the materials, implementation and review actions (Cerezo et al., 2020), strategies for organizing the learning context and requesting peer support (Pierrot et al., 2021), strategies for monitoring performance and self-adaptation tasks (Wang et al., 2022). In (Leite et al., 2022) and (Hidayah et al., 2018) they used metacognitive self-regulation strategies such as monitoring, effort regulation, and metacognition as self-testing (Leite et al., 2022).

The use of SRL strategies plays a crucial role in increasing students' academic performance in VLEs.

The diversity and scope of these strategies highlight the importance of promoting educational environments that not only recognize, but also actively encourage self-regulation, empowering students to shape their own learning experience and achieve more meaningful academic outcomes.

4.3 RQ3: How Does a Student'S Current Posture Influence Their Ability to Self-Regulate Their Learning in a VLE?

Research presents some attitudes of students that influence their ability to self-regulate. According to (Pierrot et al., 2021), dropout students do not use any SRL strategy, they procrastinate and communicate little with their peers, while follower students use some strategies, but procrastinate and start working by communicating with their peers. However, solitary performers use strategies, do not procrastinate, and do not communicate with their peers. Finally, effective students use self-regulatory strategies, do not procrastinate, and communicate with their peers. By considering students' diverse stances toward self-regulation, educators can develop more targeted and personalized strategies to effectively support students' academic development and self-regulation in educational settings.

4.4 RQ4: How to Measure SRL?

SRL can be measured by analyzing student data in the VLE. In (Afzaal et al., 2021), SRL was evaluated by analyzing student performance in a programming course. Initially, students' experience and motivation were assessed, followed by an analysis of the attributes of the questionnaire and tasks related to scoring and time spent, then the attributes of activity completion were examined, including count of video views, materials, and forums, followed by an analysis of student grades. To predict future performance, tests were carried out with Artificial Intelligence algorithms, with the Artificial Neural Network (ANN) outperforming the others in all measures, although Random Forest (RF) was similar in predicting questionnaires, and K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) produced identical results across all tasks. On the other hand, Logistic Regression (LR) performed worse than the other algorithms. (Hidayah et al., 2018) also measured SRL by analyzing student data in the VLE. From the student's interaction with the system and the definition of their objectives, it was possible to develop the students' modeling in their system.

Another way to measure SRL, which also uses the analysis of student data in the VLE, is by extracting student records. In the (Cerezo et al., 2020) study, student records were extracted and related to four attributes: time, student identifiers (ID), action, and information. SRL can also be measured by collecting types of learning information from students. In (Wang et al., 2022), it was measured using the PQ and KR algorithm; these algorithms separate questions and quiz options, making it easy to automatically generate personalized quizzes for each student. Student performance is monitored through responses to quizzes; the separation between questions and options allows for the dynamic creation of custom quizzes and questions. The system provides adaptive feedback based on the student's knowledge by connecting knowledge concepts directly to quiz options. Learning materials are linked to quiz options, making it easy to identify knowledge gaps or errors. The system also provides accurate feedback for wrong answers and recommends additional content when students respond correctly.

Data analysis in VLE emerges as a versatile and effective tool for measuring SRL. The combination of objective methods, such as Machine Learning algorithms, with subjective approaches, such as questionnaires and scales, provides a comprehensive and meaningful view of the students' self-regulation process in the VLE. The results can guide more personalized and effective pedagogical practices and teaching strategies.

4.5 RQ5: Which Datasets Are Used in Research?

All articles used real student data collected from VLEs with information about students' educational activities during a course. The VLEs used were Moodle (Cerezo et al., 2020; Wang et al., 2022), nStudy (Odilinye and Popowich, 2020), exercise platform (Pierrot et al., 2021), personalized assisted mobile system (Wang et al., 2021) and Math Nation (Leite et al., 2022). (Afzaal et al., 2021) and (Hidayah et al., 2018), did not specify the name of the VLE used.

In (Afzaal et al., 2021; Hidayah et al., 2018; Pierrot et al., 2021) VLE data from students in the computing area were used. In (Wang et al., 2021) data from pre-test and post-test scores were used, from randomly selected students. (Cerezo et al., 2020)'s research used data from undergraduate students from an online course on Moodle. VLE logs were extracted from real events (time, student ID (to maintain anonymity), action, and information), which were relevant to the process of self-regulation of learning and academic performance of the course.

The (Hidayah et al., 2018) research also used student interaction log data in the VLE, but the VLE used was another unspecified one. In (Leite et al., 2022) data from Math Nation was utilized and integrated into the student information system. In (Wang et al., 2022) two datasets were used, a small dataset with 1,000 students and 10,000 question options, and a large dataset with 10,000 students and 100,000 options. In (Odilinye and Popowich, 2020) data from 49 undergraduate students from a Canadian university were used.

Data collection in VLEs provides a solid basis for investigating SRL in diverse educational environments. The interdisciplinary approach and the variety of analyzed data contribute to a comprehensive understanding of SRL, providing valuable information for the continuous improvement of teaching and learning methods.

5 RESULTS - RESEARCH OPPORTUNITIES (RQ6)

In this section, we check what the selected/reviewed papers suggest as future work and identify the opportunities found for future research.

One suggestion is to use experiments on larger data sets and collaboration with teachers to determine the effectiveness of the proposals presented (Afzaal et al., 2021). Another is to implement and test the functionality of recommending the use of SRL strategies in a classroom environment with students (Hidayah et al., 2018). More research is needed to understand which design features lead students to believe which visualization is easier to use. Better understand students' motivations for using these services and how best to adapt design and implementation to their needs (Pierrot et al., 2021). Future research can investigate how the integration of other VLE functionalities can be included in a personalized learning recommendation system, such as collaborative learning and question generation module (Odilinye and Popowich, 2020).

One need is to incorporate more natural language processing functions into the VLE. Teachers can be assisted with questions about a given domain. Collect new types of student learning information for deeper machine learning analysis, such as the time taken to answer questions, feedback, and number of hits from recommended resource links (Wang et al., 2022). Another future work is to shift focus to other relevant VLEs, such as MOOCs, and check findings across different types of learning platforms (Cerezo et al., 2020).

It is also important for future studies to consider students' learning characteristics, such as their cognitive learning styles or types of SRL and examine whether students of various learning profiles would benefit differently from this system (Wang et al., 2021). Other SRL strategies, such as help-seeking or peer learning, can be used. Future research could include more SRL strategies and investigate whether teacher instrumental orchestration continues to moderate the relationship between student SRL and student achievement (Leite et al., 2022).

We detected that self-regulation construct surveys have been carried out using several questionnaires, often adapted to the specific needs of the authors. A specific SRL questionnaire for VLEs that can briefly calculate these indicators could be a point of advancement in research that uses SRL. Another possibility is to integrate VLEs with SR mechanisms and recommend educational objects to improve student performance.

6 FINAL CONSIDERATIONS

The application of metacognitive strategies and the development of adaptive algorithms result in personalized recommendations, positively influencing academic performance and strengthening SRL. SRL not only affects test scores, but also contributes to the achievement of specific educational goals.

Projects such as alert systems and personalization of online environments based on SRL behaviors have a positive impact by predicting at-risk students and providing a more effective learning experience. Measuring learning Self-regulated is possible through the analysis of data generated in VLEs. Studies highlight the continuous need to integrate and improve SRL strategies in VLEs. Students' active and conscious promotion of SRL contributes not only to academic development but also reflects an engaged, in-depth engagement with the learning material.

This article provides a comprehensive overview of SRL use over the last 5+ years (2018-2023), highlighting measures and strategies for assessment. Its findings stemmed from answers to 6 Research Questions. Taken together, the answers provided an overview of the state of the art and supported an indication of research opportunities. The main findings and opportunities for research were as follows. Understanding students' motivations for using VLEs and personalizing the design and implementation according to their needs; The incorporation of NLP functions in VLEs Future research should focus on how these NLP can support teachers in this process.

This work contributed to providing more insight into how SRL has been used over the years in education, seeking to highlight how self-regulation is measured, which self-regulation strategies are used and what is the impact of SRL on student performance. Regarding future work, we hope to see more experiments on improving student performance and motivation using SRL strategies.

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