International Journal of Assessment Tools in Education
2024, Vol. 11, No. 4, 675–698
https://doi.org/10.21449/ijate.1502786
journal homepage: https://dergipark.org.tr/en/pub/ijate **_Research Article_**

Self-regulated learning support in technology enhanced learning environments: A reliability analysis of the SRL-S rubric

Slaviša Radović[1*], Niels Seidel[1]

[1]Center of Advanced Technology for Assisted Learning and Predictive Analytics (CATALPA), FernUniversität in Hagen, Germany

ARTICLE HISTORY

Received: June 20, 2024

Accepted: Sep. 14, 2024

Keywords:

Self-regulated learning,
SRL-S rubric,
Validity,
Reliability.

Abstract: Advanced learning technologies have become a focal point in recent educational research, holding the promise of enhancing students' self-regulated learning (SRL) by facilitating various processes of planning, monitoring, performing, and reflecting upon learning experiences. However, concerns have arisen regarding the efficacy and design of technologies, the spectrum of possibilities for SRL support, and too ambiguous claims associated with these technologies. To address these uncertainties and to provide a platform for generating the more empirical evidence, Self-Regulated Learning Support (SRL-S) rubric was developed to facilitate the assessment of SRL support in technology-enhanced learning environments. It is grounded in established educational theory and proven empirical research results. This article presents a study that extends the application of the rubric to establish its reliability and validity, filling a gap in prior research. First, content, criterion-related, and construct validation were performed through international and interdisciplinary experts' reviews. Subsequently, inter-rater and intra-rater reliability were assessed using Intraclass Correlation Coefficients and Cohens Kappa tests. The outcomes of these analysis demonstrated that the SRL-S is a reliable and valid instrument for assessing the levels of SRL support within learning environments. Additional implications for further research to support self-regulated learning are discussed.

1. INTRODUCTION

Over the last two decades, there has been a substantial advance in offering online and distance learning environments within higher education (Ameloot et al., 2024). This trend can be attributed to several factors, including the evolving demands of the labor market, the increasing importance of lifelong learning, and the innate desire of individuals to acquire knowledge (OECD, 2019; Mirriahi et al., 2018). Consequently, numerous higher education institutions have taken proactive steps to organize learning materials and offer educational opportunities tailored to diverse groups of students, thereby ensuring the provision of inclusive and high-quality education for all (Wu et al., 2023).

These modern distance and online learning environments (LE) exhibit a range of distinctive advantages. For example, a notable benefit is the flexibility they afford students, granting them the freedom to choose when, what, and where they learn. Additionally, these environments

*CONTACT: Slaviša RADOVIĆ ✉ slavisa.radovic@fernuni-hagen.de FernUniversität in Hagen, Universitätsstr. 11 – IZ / Building 3, Room 2G 13 (2nd floor), 58097 Hagen, Germany

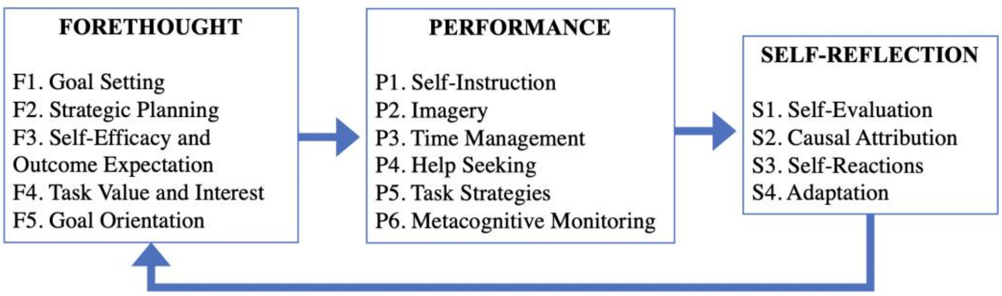
e-ISSN: 2148-7456

attract a diverse array of students, each possessing varying levels of prior knowledge, professional experience, and expertise (Mirriahi et al., 2018). Furthermore, they use a specific strategy that requires less direct guidance from instructors (Zimmerman, 2008), fostering greater autonomy among students and providing convenient access to a wide spectrum of learning resources. Despite the apparent benefits, its effectiveness can vary among students including high dropout rates, procrastination, and the long study duration (Goda et al., 2022). While some excel, others may face challenges (Wu et al., 2023).

Empirical research has shown that the acquisition of self-regulated learning (SRL) skills has assumed a critical role in fostering effective and efficient learning (Jivet et al., 2017; Sghir et al., 2022). SRL encompasses a multifaceted set of strategies and learning processes that encompass goal setting, continual progress monitoring, adaptive behavioral adjustments, comprehensive outcome assessment, and reflection (Wu et al., 2023). Students who proactively take control of their own learning processes tend to experience a wide array of academic and non-academic advantages when compared to their peers who are less self-regulated. Nevertheless, many students encounter difficulties when it comes to self-regulation practices. They often struggle with reflective thinking and face challenges in effectively monitoring their progress in alignment with their learning objectives (Radović et al., 2024b). This issue has received significant attention and recognition in academic literature.

From an academic standpoint, SRL has been a widely examined theoretical construct that delineates the cognitive, motivational, and behavioral strategies employed by learners to oversee and govern their own learning processes and results (Zimmerman, 2008; Lodge et al., 2019; Pintrich, 2000). Among the influential models within this domain is Zimmerman's SRL model, which drew upon the foundational work of Bandura and Pintrich. Zimmerman's model articulates three distinct phases in the SRL process: firstly, the thought phase, during which learners set objectives, gauge their motivation levels, and engage in task analysis processes like goal establishment and strategic planning; secondly, the performing phase, wherein learners concentrate their attention, actively participate in tasks, and continually monitor their progress; and lastly, the self-reflection phase, where learners critically assess both the task at hand and their own performance, culminating in comprehensive self-evaluation and self-assessment (Zimmerman, 2008). The complexity of the SRL process and the necessity of aiding students in developing these essential skills has become a paramount concern in both practical educational settings and academic discourse (Wu et al., 2023).

Figure 1. *The phases of self-regulated learning, as introduced in Zimmerman (2000) model, with corresponding learning processes and strategies (Radović & Seidel, 2024a; 2024b).*



In light of previous concerns, the remainder of our paper is structured as follows: Section 2 first delves deeper into a range of advanced learning technologies used to effectively and efficiently support students' SRL in distance and online higher education learning environments. Here the focus will be particularly on those technologies based on learning analytics and data mining. The section will then explain the challenging aspect of the SRL support reflecting possible spectrum of variability. Section 3 outlines the research questions addressed in this study, while Section 4 details the research methodology used for data collection and analysis. In Section 5, we present our findings and engage in a comprehensive discussion of the results. Finally, the article concludes by considering its limitations and offering directions for future research.

2. SRL SUPPORT IN LEARNING ENVIRONMENTS

In light of the growing significance of the SRL concept, which, owing to its intricacies, presents a multifaceted challenge, the endeavor to aid students in cultivating these skills remains a central issue for educators and researchers worldwide (Andrade & Du, 2007; Lodge et al., 2019; Mirriahi et al., 2018; Radović et al., 2024a). Empirical research has unequivocally demonstrated that when supported, learners can make substantial progress in enhancing their ability to strategize, monitor, and assess their own learning processes (Ameloot et al., 2024; Goda et al., 2022).

Therefore, various frameworks and advanced learning technologies have emerged in this pursuit, including personalized education, intelligent tutoring systems, adaptive learning systems (Wu et al., 2023; Wang et al., 2023). Insightful review studies conducted by Molenaar et al. (2023), Jivet et al. (2017), Sghir et al., (2022) and other scholars have illuminated a set of specific technological features within learning environments that have proven to be highly effective. These encompass the integration of learning analytics dashboards, provision of support for goal setting, incorporation of self-assessment features, facilitation of guidance for student reflection, and the implementation of personalized recommendations. Refer to Table 1 for a brief overview, and consult the comprehensive review provided by Radović and Seidel (2024a).

Table 1. *Advanced learning technologies within learning environments that have proven to be effective for self-regulated learning support.*

Feature	Description
Learning analytics dashboards (LAD)	Learning analytics and data mining techniques can be effectively utilized to develop learning analytics dashboards, as demonstrated by Jivet et al. (2017) and Radović et al. (2024b). These dashboards provide visual summaries of various learning metrics, encompassing factors such as correct and incorrect response rates, time allocation for activities, overall progress, and behavioral patterns (Ameloot et al., 2024; Dong et al., 2024). These metrics can be personalized and adapted to the learner, the learning process, and the learning context. Integrating such features into educational settings empowers students to actively monitor and manage their own learning experiences, as highlighted by Wang et al. (2023). Students can align their efforts with personalized learning plans, assess their progress, and make necessary adjustments for similar tasks in the future, as suggested by Jivet et al. (2017).
Goal setting support	Recent comprehensive reviews conducted by Dong et al. (2024) and Jivet et al. (2017) underscore the critical importance of students' ability to select and adapt goal orientations throughout their learning journey. In educational environments, it is essential to design tools and features that assist learners in explicitly defining goals and benchmarks for their learning activities within the curriculum. These support for goal setting should encompass a wide array of performance indicators, progress markers, effort allocation, and criteria for success. It's crucial that these tools effectively integrate the diverse range of learning materials available, including readings, tasks, and self-assessment activities (Radović et al., 2024b). For students, the process of choosing and establishing goals serves two fundamental purposes. Primarily, it offers them guidance and a sense of purpose, influencing their planning and shaping their future actions (Sghir et al., 2022). Secondly, it empowers them to monitor their progress, assess the efficacy of their strategies, and make necessary adjustments to ensure the attainment of their goals.

Reflection support	Reflection is a pivotal component of Self-Regulated Learning (SRL), as briefly noted earlier (Panadero, 2017). It's a cognitive and emotional process, through which learners critically assess their progress, effort, and adapt their learning strategies (Andrade & Du, 2007; Radović, 2024). While reflection is complex and demands initiation, time, and effort, instructions and guiding questions can assist learners in developing reflective thinking skills and becoming more adept at reflective practice (Jivet et al., 2017). Furthermore, directing reflective thinking towards specific learning goals or potential challenges can help learners maintain focus and avoid irrelevant exploration (Zimmerman, 2008).
Self-assessment support	Self-assessment is a crucial strategy in higher education, empowering students to independently evaluate their understanding and proficiency in a subject (Andrade & Du, 2007; Panadero et al., 2016). It promotes self-regulated learning by increasing awareness of the learning process and individual responsibility - students review their work, identify performance gaps, and assess against predefined criteria. Additionally, analyzing students' performance and progress in relation to their chosen learning goals, could additionally provide valuable feedback, empowering students to adjust their learning strategies accordingly (Radović et al., 2024a; Wang et al., 2023).
Practical recommendations	Adaptive and personalized learning environments are designed to assist learners by tailoring content to their specific needs (Wang et al., 2023). Visual cues can aid learners in adjusting their plans to achieve their goals, but these recommendations are meant to complement, not replace, the SRL process (Ameloot et al., 2024). This is especially valuable for students who face difficulties in self-regulated learning or need additional guidance (Dong et al., 2024). This supplementary support can be particularly beneficial for students who may face challenges in practicing SRL, lack clear direction in their learning, experience disorientation or cognitive overload when pursuing their goals, or struggle to identify alternative strategies and strategically plan their learning (Lodge et al., 2019; Radović et al., 2024b). Adaptive and personalized learning environments aim to help learners navigate the complexity of their educational journey by tailoring content to their specific needs at any given moment (Wang et al., 2023).

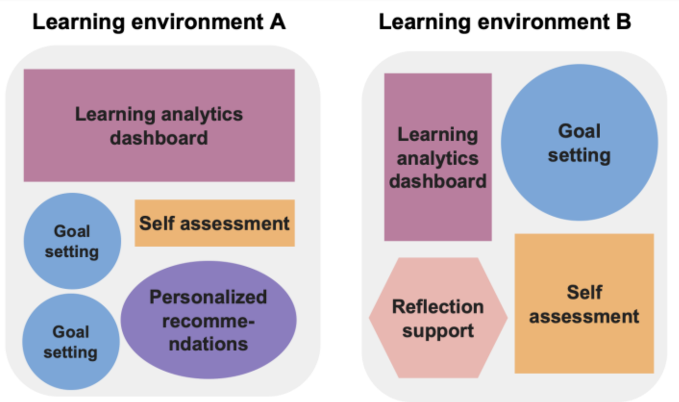
2.1. Spectrum of SRL Support

It is widely acknowledged that in order to effectively guide learners through all phases of the SRL cycle, a learning environment must provide a comprehensive and cohesive array of technological features (Radović et al., 2024b). Nevertheless, previous research efforts have often narrowly focused on specific aspects of support. For instance, some studies have concentrated on implementing learning dashboards or only incorporating self-assessment tasks (Pérez-Álvarez et al., 2018; Jivet et al., 2017). Additionally, literature reviews have highlighted an uneven emphasis on different phases of the SRL process, with certain learning environments claiming to support SRL by emphasizing self-monitoring but overlooking self-reflection phase, or vice versa (Goda et al., 2022; Heikkinen et al., 2022).

It has also become evident that SRL support is not a binary concept but rather exists along a spectrum. A recent empirical study conducted by Radović et al (2024b), comparing two learning environments with differing levels of SRL support, revealed that depending on technological features, the levels of SRL support can range from limited to advanced. The results of this study acknowledge that different levels of SRL support can differentially affect students' learning progress and outcome (Radović et al., 2024b). Another research study conducted by Goda et al. (2022) delved into the effects of two learning environments. Case 1 involved an early warning system predicting potential student dropouts, while Case 2 focused on student planning and implementation phases within the self-regulated learning cycle. Their comparison revealed distinct differences, highlighting that an early warning system requiring pre-learning planning could reduce the necessity for teacher intervention, decrease procrastination tendencies, and result in heightened learning outcomes.

Discrepancies may arise in the developmental scope and feature availability of educational settings, as highlighted by Sghir et al. (2022). Consequently, these variations can influence the level of support they offer for self-regulated learning, as visually depicted in Figure 2 and discussed by Radović and Seidel (2024a). Let's consider Learning Environments A and B, which share identical curriculum content and employ similar technologies. Despite these similarities, the divergence in their support for self-regulated learning becomes evident (Radović and Seidel, 2024a; 2024b; Radović et al., 2024b). Although both environments incorporate sophisticated learning technologies to enhance students' self-regulation, differences in their implementation methods and extents may lead to varying levels of support for self-regulated learning. However, the extent to which these distinctions between the two learning environments are substantial, relative, or absolute, and their potential impact on disparate learning outcomes and processes, remains unverified in the existing research literature. This variability in self-regulated learning support within learning environments poses a significant challenge for researchers and educators, complicating efforts to comprehensively understand and compare diverse developments in this field (Radović et al., 2024b).

Figure 2. *Simplified example of difference between two learning environments.*



2.2. Rubric for Evaluating the Spectrum of SRL Support

To bear with this challenging aspect of the spectrum of SRL support, Radovic and Seidel (2024a) introduced the rubric, designed to assess the degree of self-regulated learning support available within technology enhanced learning environments (Figure 3 and Appendix A). It is strongly grounded in the theoretical Zimmerman's model (Panadero, 2017) and empirical results distilled from review studies (e.g. Jivet et al., 2017; Pérez-Álvarez et al., 2018; Viberg et al., 2020) that have demonstrated significant effectiveness in supporting student self-regulation. Rubric development process included several phases that will be disclosed in the following text.

First, the structure of the SRL-S rubric was developed by mapping the phases of Zimmerman's SRL model (Forethought, Performance, and Self-Reflection) to the dimensions of the rubric (with same titles). Each phase of Zimmerman's model contains multiple learning strategies; for example, the Forethought phase includes Goal Setting, Strategic Planning, Self-Efficacy, Task Value and Interest, and Goal Orientation. These strategies were incorporated as items in the SRL-S rubric (for the corresponding dimension). Therefore, following the SRL model (see Figure 1), our rubric consists of 14 items across the three dimensions: Forethought (F1. Goal Setting, F2. Strategic Planning, F3. Self-Efficacy, F4. Task Value and Interest, F5. Goal Orientation), Performance (P1. Self-Instruction, P2. Imaginary, P3. Time management, P4. Help Seeking, P5. Task Strategies, P6. Metacognitive monitoring), and Self-Reflection (S1.

Self-Evaluation, S2. Casual attribution, S3. Self-reactions, S4. Adaptation). Additionally, each of the items (learning strategies) has been supplemented with a brief description based on Zimmerman's theoretical model (see Table 2).

Second, we aimed to gather and analyze review studies that systematically examine the features of advanced learning technologies. Using a broad search strategy, we collected ten systematic reviews of empirical studies focused on tools that support SRL (Araka et al., 2020; Ceron et al., 2021; Devolder et al., 2012; Edisherashvili et al., 2022; Gambo & Shakir, 2021; Garcia et al., 2018; Jivet et al., 2017; Matcha et al., 2020; Pérez-Álvarez et al., 2018; Viberg et al., 2020). We examined how each technology facilitated critical aspects of SRL as outlined in the reviews, considering established clear and distinct standards for each criterion. Each feature and tool are referenced with the review study from which it originated (see the Table 2's column of practical aspects of the rubric). The first author conducted a thorough review of all the studies, identifying key features and tools and categorizing them accordingly. To quantify inter-rater agreement, the second author independently reviewed three recent studies (Ceron et al., 2021; Edisherashvili et al., 2022; Gambo & Shakir, 2021) and categorized the data. Cohen's κ was calculated to assess the level of agreement, showing agreement between the researchers' judgments with kappa value of $\kappa = .526$, $p < .001$ (with total percentage agreement of 80%). This result reflects the proportion of agreement beyond chance, and based on Altman's (1999) guidelines, indicate an acceptable moderate strength of agreement.

Table 2. *Initial structure and notes for rubric development process.*

Theoretical aspect of rubric based on Zimmerman (2000) SRL model.		**Practical aspect of rubric based on evidence from review articles examining learning technologies for SRL (see the note for full set of articles)**
Phase of SRL	**Corresponding strategies and its description**	
Forethought Phase	**F1. Goal Setting** *Establishing specific, measurable, and time-bound objectives to provide direction and motivation for learning.*	- Provide possibilities to select or define goals that focus on skill development, performance improvement, or specific learning activities (Gambo & Shakir, 2021; Jivet et al., 2017; Matcha et al., 2020). - Provide mechanisms for setting educational goals and corresponding sub-goals (Ceron et al., 2021; Matcha et al., 2020). - Offer predefined goal hierarchies and clear descriptions to guide students' navigating their learning path (Devolder et al., 2012; Viberg et al., 2020). - Empower students to define their own goals and select relevant indicators (Matcha et al., 2020). - Encourage the practice of setting and revisiting goals and sub-goals during learning process (Edisherashvili et al., 2022; Viberg et al., 2020). - Implement intelligent agents to assist students in choosing and setting goals concerning course content (Edisherashvili et al., 2022). - Supply detailed information on grading criteria and course standards (Matcha et al., 2020).
	F2. Strategic Planning *Developing a structured approach to achieving goals, including planning steps, resources, and timelines.*	- Utilize dashboard visualizations to provide multi-dimensional presentations of student progress, success, and effort (Matcha et al., 2020; Edisherashvili et al., 2022; Gambo & Shakir, 2021; Jivet et al., 2017). - Guide students toward specific activities during their learning process, ensuring alignment with educational goals (Araka et al., 2020). - Support systematic planning through the use of weekly e-journals, supplemented by prompts to encourage ongoing reflection (Edisherashvili et al., 2022). - Implement prompts that encourage planning of learning activities ahead of time, fostering better preparation and time management (Devolder et al., 2012; Edisherashvili et al., 2022). - Send reminders about progress, accompanied by explicit encouragement, to help students stay focused on their learning goals (Edisherashvili et al., 2022; Viberg et al., 2020). - Offer tools (calendar, schedule support, task list) to assist planning the sequence, timing, and completion of activities (Ceron et al., 2021). - Display a visual representation of the learning resources on the main page, making it easily accessible and serving as a constant reference (Edisherashvili et al., 2022). - Provide information on productive learning strategies (Edisherashvili et al., 2022).

F3. Self-Efficacy and Outcome Expectation *Cultivating a belief in one's ability to succeed (self-efficacy) and expectations of the outcomes of one's efforts to boost motivation and persistence.*	- Utilize dashboard to provide clear and actionable insights into learning progress, success, and effort; helping students identify areas of strength and improvement (Araka et al., 2020; Jivet et al., 2017; Pérez-Álvarez et al., 2018; Viberg et al., 2020;). - Use visualizations (such as radar graphs, line charts, heat maps, mastery grids, cloud tags, and interaction diagrams) to support analysis of learning process (Edisherashvili et al., 2022; Gambo & Shakir, 2021; Jivet et al., 2017; Pérez-Álvarez et al., 2018; Viberg et al., 2020; Matcha et al., 2020). - Send reminders about progress, accompanied by explicit encouragement, to help students stay focused on their learning goals (Edisherashvili et al., 2022; Viberg et al., 2020). - Provide opportunities for comprehension checks during and after learning activities, followed by immediate feedback (Edisherashvili et al., 2022). - Compare learners' performance with peers who have similar goals, previous graduates, top-performing peers, or teammates (Jivet et al., 2017; Pérez-Álvarez et al., 2018). - Use goals standards to describe outcomes of one's effort during learning (Jivet et al., 2017). - Predict student performance, enabling timely interventions and personalized feedback (Araka et al., 2020; Viberg et al., 2020).
F4. Task Value and Interest *Identifying and enhancing the intrinsic and extrinsic value of the task to increase engagement and effort.*	- Emphasize the relevance and usefulness of tasks to enhance their engagement with the learning material (Ceron et al., 2021). - Highlight personal significance of tasks and relation to the curriculum to make them more engaging (Ceron et al., 2021). - Prompt learners to activate their prior knowledge, facilitating connections with new material (Edisherashvili et al., 2022; Pérez-Álvarez et al., 2018). - Incorporate example-based learning through the use of real world examples and professional tools (Garcia et al., 2018).
F5. Goal Orientation *Adopting a specific orientation towards goals, such as mastery (learning) or performance (demonstrating ability), to guide learning behavior.*	- Provide students with a predefined goal hierarchy and clear descriptions to help them understand and structure their learning (Devolder et al., 2012). - Use prompts to encourage students stay mindful of their overall learning goals (Edisherashvili et al., 2022; Pérez-Álvarez et al., 2018). - Enable students to define and manage their learning paths by offering customized learning activities (Edisherashvili et al., 2022). - Use different colors to denote various aspects and qualities of learning, helping students quickly identify what need to be improved (Edisherashvili et al., 2022). - Provide features that allow students to analyze their performance against goals, giving them a clearer understanding of their standing (Edisherashvili et al., 2022; Jivet et al., 2017; Matcha et al., 2020; Pérez-Álvarez et al., 2018). - Send personalized feedback to learners to complement their achievements and encourage those who may be falling behind (Edisherashvili et al., 2022).

Performance Phase	**P1. Self-Instruction** *Using prompts or self-talk to guide one's actions and maintain focus during the task.*	- Provide adaptive support that offer timely feedback to guide learning actions (Araka et al., 2020; Pérez-Álvarez et al., 2018; Viberg et al., 2020). - Ensure that course material is presented in a well-structured manner, utilizing diverse media formats to enhance understanding and engagement (Edisherashvili et al., 2022). - Incorporate self-directed prompts to help learners navigate the platform more effectively, encouraging them to reflect about their learning strategies and actions (Edisherashvili et al., 2022). - Implement automated self-assessments that allow comparison of answers with teacher-prepared solutions (Garcia et al., 2018).
	P2. Imagery *Employing mental visualization techniques to rehearse or envision successful task completion and problem-solving.*	- Facilitate students use of concept-mapping tasks to help them organize and visualize knowledge (Devolder et al., 2012; Pérez-Álvarez et al., 2018). - Incorporate mind-mapping tools that aid in mental visualization (Devolder et al., 2012). - Provide a variety of instructional materials (e.g., watching, discussing, conceptualizing, trying out) and allow learners to choose the modes of instruction and materials (Edisherashvili et al., 2022). - Encourage active learning engagement through tools such as text highlighting, annotation, and summarizing (Edisherashvili et al., 2022; Garcia et al., 2018).
	P3. Time Management *Allocating and managing time effectively to balance task demands and ensure timely completion.*	- Assist students in estimating the time required to complete activities (Ceron et al., 2021). - Display a visual representation of the study plan (course material) on the main page of the learning platform, providing a clear overview of tasks (Edisherashvili et al., 2022; Matcha et al., 2020). - Support learners to analyze their progress relative to their peers and teacher-set expectations, helping them organize time more effectively (Edisherashvili et al., 2022). - Monitor time spent on learning, assessments, and planning, offering insights into how students allocate their time across various activities (Gambo & Shakir, 2021; Jivet et al., 2017; Matcha et al., 2020). - Record the time and reasons for interruptions in study sessions to better understand factors affecting learning (Pérez-Álvarez et al., 2018). - Provide hints and prompts to support time management and enhance learning efficiency (Viberg et al., 2020).
	P4. Help Seeking *Actively seeking assistance or feedback from others when encountering difficulties or needing additional support.*	- Encourage students to seek help from instructors, peers, or external resources when needed (Ceron et al., 2021; Garcia et al., 2018). - Explicitly remind students of the possibility of seeking help during their learning (Edisherashvili et al., 2022). - Facilitate collaboration as a means to improve the learning process through collective input (Edisherashvili et al., 2022). - Promote the exchange of constructive peer feedback in discussion forums (Edisherashvili et al., 2022; Gambo & Shakir, 2021; Garcia et al., 2018; Matcha et al., 2020). - Create an open forum where students can share their thoughts and work-in-progress (Edisherashvili et al., 2022), as well as final product (Edisherashvili et al., 2022; Gambo & Shakir, 2021; Garcia et al., 2018). - Use pedagogical agents to encourage help-seeking, guiding students to resources and support (Gambo & Shakir, 2021).

		- Incorporate social networks, wikis, blogs, discussion forums or shared learning spaces to facilitate support (Pérez-Álvarez et al., 2018).
	P5. Task Strategies *Applying specific methods or techniques relevant to the task to enhance performance and achieve goals.*	- Advice students in organizing, planning, and managing their study time and tasks, including time allocation, sequencing, and reorganization of instructional materials (Ceron et al., 2021). - Provide criteria and solution to tasks (Edisherashvili et al., 2022; Garcia et al., 2018), as well as hints and feedback to help students understand and correct their errors (Devolder et al., 2012). - Include worked-out examples to illustrate problem-solving methods and concepts (Devolder et al., 2012). - Implement strategies such as sketching (Ceron et al., 2021), mind-mapping, and visualization (Devolder et al., 2012). - Encourage the interpretation, analysis, evaluation, and critical thinking during solving complex problems (Ceron et al., 2021). - Offer guidance on the problem-solving steps students can take (Garcia et al., 2018; Devolder et al., 2012). - Provide hints to students on how to proceed when they encounter errors, (Garcia et al., 2018). - Supply information on effective and efficient learning strategies (Matcha et al., 2020). - Encourage active learning engagement through tools such as text highlighting, annotation, and summarizing (Edisherashvili et al., 2022; Garcia et al., 2018).
	P6. Metacognitive Monitoring *Continuously students one's own cognitive processes, such as understanding and adjusting strategies based on progress and difficulties.*	- Inform students in real time about their knowledge gains, enhancing awareness of their capabilities and progress (Ceron et al., 2021). - Prompt students to assess their understanding (eg. self-assessment task, quizzes, tests) (Edisherashvili et al., 2022; Jivet et al., 2017). - Prompt students to evaluate their behavioral engagement with learning units and different learning materials (Edisherashvili et al., 2022). - Send personalized emails to compliment students on their achievements or encourage those who are falling behind (Edisherashvili et al., 2022). - Process learner activity to provide visual summary, estimate progress, and feedback for improvement (Edisherashvili et al., 2022; Garcia et al., 2018; Jivet et al., 2017; Matcha et al., 2020). - Provide dashboard indicators to help students track their progress towards achieving set goals (Gambo & Shakir, 2021; Garcia et al., 2018; Viberg et al., 2020).
Self-Reflection Phase	**S1. Self-Evaluation** *Reflecting on and assessing the effectiveness of one's performance and strategies in achieving goals.*	- Provide prompts to encourage learners to reflect on their learning experiences (Viberg et al., 2020). - Provide predictions of students' performance to help them gauge their progress (Araka et al., 2020; Jivet et al., 2017). - Provide feedback regarding the productivity and relevance of the learning activities (Edisherashvili et al., 2022; Araka et al., 2020) - Offer opportunities for knowledge tests during and after learning activities (Edisherashvili et al., 2022; Gambo & Shakir, 2021). - Provide a visualization and use of different colors to denote various aspects and qualities of learning process (Edisherashvili et al., 2022; Pérez-Álvarez et al., 2018; Viberg et al., 2020).

	- Analyze students' performance against expectations (eg. standards or class averages) to provide benchmarks for reflection (Edisherashvili et al., 2022; Gambo & Shakir, 2021; Jivet et al., 2017). - Implement a social comparison feature that allows learners to analyze their progress in relation to their peers (Edisherashvili et al., 2022; Jivet et al., 2017).
S2. Causal Attribution *Identifying and analyzing the reasons behind successes or failures to understand the factors influencing performance.*	- Provide information that helps learners assess their ability to complete tasks, enhancing their self-awareness and confidence (Ceron et al., 2021). - Incorporate self-assessment and feedback process to encourage students to examine their misunderstanding (Devolder et al., 2012). - Provide dashboard information on previous learning problems, failures, or challenges (Jivet et al., 2017; Matcha et al., 2020). - Use reflection tasks to support learners in planning, setting goals, and reflecting on their learning processes (Edisherashvili et al., 2022; Viberg et al., 2020). - Provide information about areas needing adaptation (Edisherashvili et al., 2022; Matcha et al., 2020).
S3. Self-Reactions *Evaluating personal reactions to performance outcomes, such as satisfaction, frustration, or motivation, to guide future efforts.*	- Address affective reactions in reflection tasks to help students understand and manage their emotional responses (Ceron et al., 2021). - Provide clear and well-defined expectations for upcoming learning experiences (Edisherashvili et al., 2022). - Increase students' awareness of their emotions by presenting insights from previous learning sessions, which can help them manage their emotional responses (Garcia et al., 2018). - Utilize awareness and dashboard visualizations to address misunderstanding, false expectations, and deactivate negative emotions (Jivet et al., 2017; Matcha et al., 2020).
S4. Adaptation *Adjusting goals, strategies, and approaches based on reflections and evaluations to improve future learning and performance.*	- Provide predictions of students' performance to help them understand their potential outcomes and areas for improvement (Araka et al., 2020). - Enable students to analyze their learning process in relation to goals (Ceron et al., 2021; Viberg et al., 2020). - Incorporate reflection questions and 'look back' prompts to encourage students to think about their future learning (Devolder et al., 2012). - Ask students to reflect on challenges encountered during learning and analyze strategies used or not used to address those challenges (Edisherashvili et al., 2022; Matcha et al., 2020). - Provide feedback (personalized messages) for current problems or suggest goals corrections (Gambo & Shakir, 2021). - Offer information for learning strategies that support learning process (Araka et al., 2020; Viberg et al., 2020).

Note: A set of review articles (Araka et al., 2020; Ceron et al., 2021; Devolder et al., 2012; Edisherashvili et al., 2022; Gambo & Shakir, 2021; Garcia et al., 2018; Jivet et al., 2017; Matcha et al., 2020; Pérez-Álvarez et al, 2018; Viberg et al., 2020).

Third, the next step involved setting the rubric's grading criteria into three levels: Limited, Moderate, and Advanced SRL support. For each rubric item, contextualized notes (as shown in Table 2) were organized in three groups to distinctly structure different criteria (Limited, Moderate, and Advanced). Then, we provided description of standards in a more decontextualized manner (see Figure 3 for an example and the full rubric in Appendix A). This decontextualization will allow rubric to be applied across various learning environments, situations, conceptual paradigms, and for different research inquiries. To write these criteria descriptions, we again reviewed theoretical articles by Panadero (2017), Pintrich (2000), and Zimmerman (2000). This iterative process (of theoretical and empirical work) aligns with the recommendations of the National Council on Measurement in Education (NCME) Standards (AERA, 2014).

Figure 3. *The part of the SRL-S rubric shows only two SRL criteria (F1 from Forethought and S2 from Self-Reflection phase) with corresponding performance levels.*

Phase	Process	Limited SRL support (1)	Moderate SRL support (2)	Advanced SRL support (3)
Forethought	*F1. Goal Setting*	Students acquire course goals predefined by the teacher, they do not have the option to set or modify their goals within learning environment, nor can they easily access goal related performance indicators.	While students still lack the capability to set or change learning goals themselves in the learning environment itself, however they receive detailed insights about their learning concerning the course's goal.	Students enjoy the flexibility to choose from a range of learning goals (which may include course mastery or just passing) or to set custom goals (content or performance related). Additionally, students are provided with details related to the chosen goal.
Self-Reflection	*S2. Causal Attribution*	Students are offered a limited resources to reflect (e.g., knowledge tests and related rubrics). They are not guided nor supported how to reflect on performance or how to evaluate factors of failure.	Students are asked to think about their performance when self-assessing tasks' solutions against criteria. This level of support encourages students to consider the factors that influenced their failures.	Learning environment includes prompted critical reflection tasks after major learning events or learning units. These tasks ask students to think– about their performance, their strengths and weaknesses, as well as to assess their progress toward their goals.

Finally, in Appendix A, the complete SRL-S rubric, introduced by Radović and Seidel (2024a; 2024b), has been showcased and detailed. By employing the rubric, educators and researchers in charge of a learning environment can 1) gain insights into the extent of implemented SRL approaches, 2) make informed decisions to refine their pedagogical strategies, 3) further develop SRL support of learning environments, and 4) better support students on their journey towards becoming self-regulated learners (Jonsson, A., & Svingby, G. (2007).

3. RESEARCH QUESTIONS FOR THIS STUDY

To further substantiate the utility of the SRL-S rubric as an instrument for assessing the level of self-regulated learning support in educational settings, this study aims to establish both reliability and validity. According to the principles of the National Council on Measurement in Education (NCME) Standards (AERA, 2014), reliability and validity analyses are crucial for ensuring that measurement tools are accurate, consistent, and fair. While validity ensures that the tool measures what it is supposed to measure and confirms that it is appropriate and meaningful for the specific context (AERA, 2014, p. 11), reliability refers to the consistency of measurement results over time and across different populations (AERA, 2014, p. 43). These analyses support the ethical and professional use of assessments, guiding effective decision-making and promoting equity in educational and psychological contexts, as emphasized by the NCME standards. Given the absence of such extensive analysis in prior empirical research, it is imperative to ascertain the effectiveness and efficiency of the rubric as a measurement tool (Reddy & Andrade, 2010; Moskal & Leydens, 2000; Thaler et al.,2009).

Hence, the primary research question under investigation in this study is as follows: Does SRL-S rubric demonstrate sufficient reliability and validity for its use to measure self-regulated learning support within online learning environments?

4. METHOD

4.1. Validity Analysis

According to the standards of American standards (AERA, 2014, p. 11), validity is a critical concept in assessment, referring to the extent to which evidence and theory support the interpretations of scores for their intended purposes. The NCME standards classify different types of evidence that can be used to support the validity of a test. These include Content, Construct, and Criterion-related Validity (AERA, 2014, p. 14, 66, 173).

4.1.1. *Participants*

As per the guidelines of the standards, the rubric's validity was assessed through a process of expert judgment (AERA, 2014, p. 25). This ensured that the rubric was both representative of and appropriate for the intended construct (Reddy & Andrade, 2010).

In the first phase, an expert discussion was initiated after the presentation of SRL-S rubric during the scientific meeting of members of CATALPA research center (Center of Advanced Technology for Assisted Learning and Predictive Analytics) of FernUniversität in Hagen in Germany. The group comprised 15 researchers, teachers, and professors who engaged in the use and development of diverse tools aimed at supporting students' self-regulation in research and teaching activities.

In the second phase, feedback on validity of developed rubric was solicited from four distinguished higher education professors, each with extensive research experience and proven excellence in self-regulated learning, learning analytics, and data mining, as evidenced by their numerous academic publications. Our aim was to incorporate interdisciplinary expertise and consider diverse geographic and cultural perspectives (Moskal & Leydens, 2000).

4.1.2. *Procedure*

According to the NCME, the experts consulted were asked to make a *Content* assessment (evidence that the rubric content is representative of the domain it's intended to cover and identifies any potential gaps or redundancies), *Construct* assessment (evidence that the rubric accurately measures the theoretical construct it claims to measure), and *Criterion-related* assessment (evidence indicating the extent to which rubric scores correlate with practical development, and the degree to which this is adequately informative) of the developed rubric's criteria and performance levels. Moskal and Leydens (2000) also noted that these are an important aspect of consideration because they examine the extent to which the rubric incorporates the knowledge and technological development of the field that is of interest for a variety of interdisciplinary experts interested in SRL support.

Experts received a set of questions evaluating whether the rubric criteria accurately represent technological development, effectively measure the theoretical construct of SRL, and whether any critical elements are missing (to align with practical development). Additional questions were set for exploring the degree of clarity in the wording, the suitability of the indicator to assess a learning environment, and the relevance of different SRLs levels (e.g. Question 3. Do you clearly understand different levels for each criterion? What was difficult to comprehend? Question 4. Is there a SRL support strategy you consider important that we leave out? To what criteria and performance level it belongs?).

4.2. Reliability Analysis

According to NCME standards, reliability refers to the degree of consistency and reproducibility of test results across different times and raters (AERA, 2014). The reliability analysis aimed to ensure that test scores accurately reflect the construct being measured. This involved two key methods: Inter-Rater Reliability (AERA, 2014, p. 44), which measures the consistency of scores assigned by different raters or judges and is crucial for subjective assessments, and Test-Retest Reliability (AERA, 2014, p. 44), which assesses the stability of test scores over time by administering the same test to the same group on different occasions.

4.2.1. *Participants*

First, four faculty members, comprising researchers who were involved in teaching or researching the same course at a distance university in Germany, independently utilized the rubric to evaluate the level of SRL support their course's digital learning environment provided to students. Second, to analyze consistent scoring across time, two of the researchers were asked to re-evaluate the learning environment two months after the first rating.

Since the evaluators needed to possess a profound understanding of learning material, all details of implemented technological features, and specific pedagogical strategies (for example for goal setting, help seeking, or reflection see Appendix), only teachers and researchers directly involved in the course with profound understanding were being able to make relevant assessment. Expanding the pool of participants was not feasible because individuals unfamiliar with the intricacies of the course would not be able to effectively use the rubric for evaluation purposes. Expanding the number of learning environments used for evaluation was also not feasible because these four evaluators would not be familiar with all the features of the learning environments. More on this later under Limitations and Future Research.

4.2.2. *Procedure*

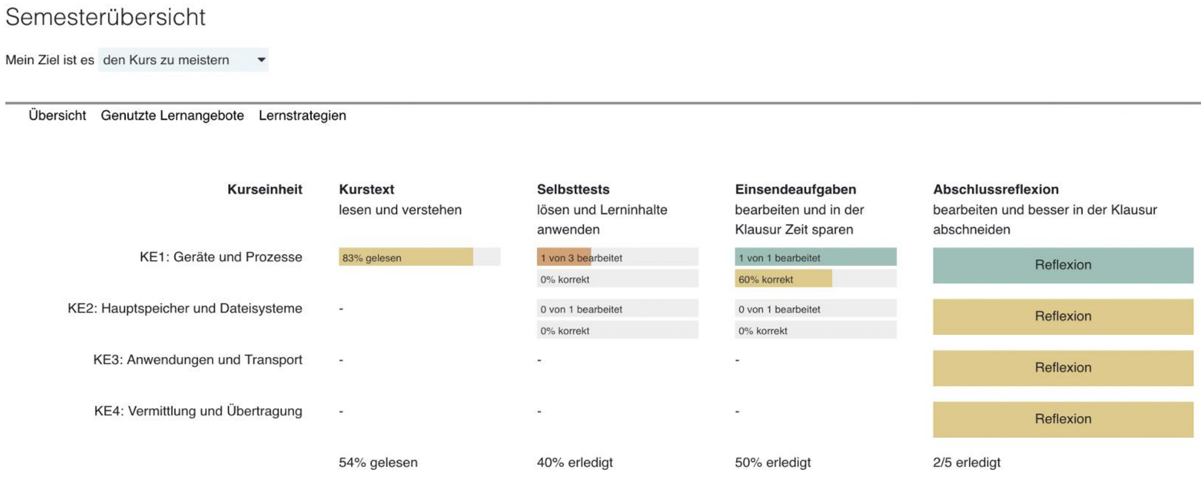
In this study, we employed a comprehensive approach to assess the reliability of the data generated, utilizing several strategies closely paralleled those utilized in prior research by Harris et al. (2010), Tabachnick and Fidell (2019), and Moskal and Leydens (2019), as well as consistent with NCME standards (AERA, 2014). Because we aimed to include more than two raters, instead of Cohen's kappa coefficient (for two raters) the Intraclass Correlation Coefficient (ICC) was used as the method (Thaler et al., 2009) to compute the interrater reliability of the rubric. This statistical measure, derived from the analysis of variance and based on mean squares representing population variances, has been widely employed to gauge interrater reliability when more than two raters were employed (Tabachnick & Fidell, 2019). In our analysis, the two-way absolute agreement model was applied to compute ICC (McGraw & Wong, 1996).

Additionally, to examine the stability of the rubric's performance over time, we assessed its intra-rater reliability. This involved **first** analyzing the percentage agreement between scores assigned to the same learning environment by the same researchers, two months apart; and **second**, calculating Cohen's kappa (κ) coefficient for these two sets, offering a quantitative measure of the test-retest reliability as suggested in work of Moskal and Leydens (2019).

4.3. Learning Environment Used for Rating

The rubric was used to score the course that was specifically designed to foster students' SRL as a component of the completely distance and online bachelor's degree programs in Computer Science at the FernUniversität in Hagen in Germany. During a period of 11 weeks students worked individually, by studying material and doing designed assignments, after which they completed the course by doing the final exam. Specific features were developed to support students' regulation: Dashboard learning overview, Reflection assignments, Self-assessment tasks along with the criteria and feedback, Goal setting feature, and Reading support (Radović et al., 2024a; Radović et al. 2024a).

Figure 4. *Dashboard for the learning environment which indicates the progress and performance per type of course material for each course unit including an ultimate reflection task. In the upper left corner, there is a dropdown menu that offers various goals.*



An overview page with a Learner Dashboard served as a collection of all learning resources, such as reading materials and various tasks. These resources were neatly organized by course units in rows, allowing students to easily monitor their progress and access available learning materials with a quick glance (Radović et al. 2024a; 2024b). To enhance student self-regulation, the learning resources were categorized by material type. Furthermore, each learning material was accompanied by two indicators, where applicable: "progress" indicated the extent of completion, while "success" reflected the accuracy or achievement in related activities. To provide personalized support, the learning environment introduced a color-coded scheme. This scheme aimed to align students' progress and success with their individual goals. Green highlighted activities in harmony with the set goal, yellow flagged potential issues, and orange indicated performance inconsistencies (Radović et al., 2024a). The feature for setting goals was presented as a user-friendly drop-down menu just below the Semester overview title (see Figure 3). This allowed students to select from three course goals: Mastery of the content, passing the course, or simply gaining an overview, representing their intention to pursue exams or desired performance. Learning overview dashboard included an additional feature: a reflection prompt located at the end of each course unit (positioned in the fourth column on the right side of Figure 1). This prompt aimed to guide students' reflective thinking toward specific learning objectives or potential learning dilemmas. It assisted students in maintaining focus on their goals, overall satisfaction, and effective learning strategies. Furthermore, self-assessments provided students with supplementary information, including the difficulty level, achieved score, and maximum score, during both the performance and thought phases (Radović et al. 2024b).

5. RESULTS AND DISCUSSION

5.1. Validity of the SRL-S Rubric

The construct validity of the initial draft of the rubric received in general strong support from comments provided by all expert reviewers. The feedback (total of 40 comments) regarding description of technology integration, the associated levels, and performance indicators, including minor suggestions for different language constructs was thoughtfully considered and integrated into the rubric revision process (Moni et al., 2005; Reddy & Andrade, 2010). According to the NCME standards (AERA, 2014, p. 81), this iterative approach to refinement proved instrumental in better aligning the rubric with intended assessment goals. Expert reviewers also identified few other relevant literature and empirical findings that were thoroughly reviewed and included in the current version of the rubric.

5.2. Teachers' Interrater Reliability

The researchers' scores for the SRL-S rubric are reported in the Table 3. This table provides the actual ratings as well as the mean scores and standard deviations for each of the rubric criteria for four raters, for their ratings of the learning environment.

Table 3. *The detailed ratings of four raters.*

SRL	SRL Processes / Strategies	R1	R2	R3	R4	M	SD
Forethought Phase	F1. Goal Setting	3	2	3	3	2.75	0.50
	F2. Strategic Planning	2	3	2	3	2.50	0.58
	F3. Self-Efficacy and Outcome Expectation	2	2	2	2	2.00	0.00
	F4. Task Value and Interest	2	2	2	2	2.00	0.00
	F5. Goal Orientation	3	2	3	2	2.50	0.58
	Overall Forethought Phase	2.4	2.2	2.4	2.4		
Performance Phase	P1. Self-Instruction	1	2	1	2	1.50	0.58
	P2. Imagery	1	2	1	1	1.25	0.50
	P3. Time Management	1	2	1	2	1.50	0.58
	P4. Help Seeking	2	2	2	2	2.00	0.00
	P5. Task Strategies	2	2	2	2	2.00	0.00
	P6. Metacognitive Monitoring	2	2	2	3	2.25	0.50
	Overall Performance Phase	1.5	2	1.5	2		
Self-Reflection Phase	S1. Self-Evaluation	3	3	3	2	2.75	0.50
	S2. Causal Attribution	3	3	3	3	3.00	0.00
	S3. Self-Reactions	3	3	3	3	3.00	0.00
	S4. Adaptation	3	2	3	3	2.75	0.50
	Overall Reflection Phase	3	2.75	3	2.75		
Overall SRL support		2.3	2.32	2.3	2.38		

The intraclass correlation coefficient (ICC) was used as the method to compute the interrater reliability of the rubric (Moskal & Leydens, 2019). The ICC estimates and their 95% CI were calculated based on the average measures ($k = 4$), absolute-agreement, 2-way mixed-effects model (including systematic errors of both raters and random residual errors). The ICC score was .86, 95% CI [.71, .95], suggesting good to excellent interrater reliability between the four raters and their scores on the SRL-S. As a rule of thumb, ICC values less than 0.5 are indicative of poor reliability, values between 0.5 and 0.75 indicate moderate reliability, values between 0.75 and 0.9 indicate good reliability, and values greater than 0.90 indicate excellent reliability (Thaler et al., 2009).

Furthermore, the analysis of raters' scores of SRL-S as presented in Table 3, reveals that the raters' overall learning support ranges from a minimum score of 2.3 to a maximum score of 2.38. The results suggest that the raters scored the overall levels of SRL support in the learning environment in a very similar manner (with a margin of differences of only 3.5%).

5.3. Teachers' Intra-Ratter Reliability

Intra-ratter reliability involved first analyzing the percentage agreement between scores assigned to the same learning environment, and second examining Kappa coefficient as the extent of agreement between frequencies of two sets of data collected on two different occasions.

To determine percent of absolute agreement, we counted the instances in which raters' first and second ratings for each criterion matched (24 cases) and divided this by the total number of criteria ratings (30). This calculation demonstrates 80% absolute agreement. As a general guideline, suggested by various experts, a percentage of absolute agreement falling within the 70-90% range indicates an acceptable level of agreement (Stemler, 2004). In addition to directly comparing the percent agreement between repeated ratings, we employed Cohen's kappa (κ) test to determine the level of agreement beyond what would be expected by random chance, separately for each of the raters, R1 and R3. An analysis of reliability for the R1 rater revealed moderate agreement between the ratings (κ = .484, p = .01), while for the R3 rater, an almost perfect agreement between repeated scores was observed (κ = .899, p < .001) (Thaler et al., 2009).

Upon an examination of the scores associated with the ratings of SRL phases, as well as the overall SRL support, a consistent and almost perfect agreement regarding the Forethought Phase and the Reflection Phase becomes evident. Notably, the ratings for the Performance Phase experienced the most significant changes over the time. As a result, this influenced a change in the overall SRL support ratings, shifting from 2.3 to 2.36 and from 2.3 to 2.47. Despite these disparities, the ratings convey the very similar level of SRL support, as depicted in Table 4.

Table 4. *Rater scores and the level of absolute agreement between raters evaluating the same learning environment (first and second time), as assessed by two researchers (R1 and R3).*

SRL	SRL Processes / Strategies	R1 First	R1 Second	R3 First	R3 Second	Agreements *absolute*
Forethought Phase	F1. Goal Setting	3	3	3	3	2/2
	F2. Strategic Planning	2	2	2	3	1/2
	F3. Self-Efficacy and Outcome Expectation	2	2	2	2	2/2
	F4. Task Value and Interest	2	2	2	2	2/2
	F5. Goal Orientation	3	3	3	2	1/2
	Overall Forethought Phase	2.4	2.4	2.4	2.4	
Performance Phase	P1. Self-Instruction	1	1	1	1	2/2
	P2. Imagery	1	2	1	2	0/2
	P3. Time Management	1	1	1	2	1/2
	P4. Help Seeking	2	2	2	2	2/2
	P5. Task Strategies	2	2	2	2	2/2
	P6. Metacognitive Monitoring	2	2	2	3	1/2
	Overall Performance Phase	1.5	1.67	1.5	2	
Reflection Phase	S1. Self-Evaluation	3	3	3	3	2/2
	S2. Causal Attribution	3	3	3	3	2/2
	S3. Self-Reactions	3	3	3	3	2/2
	S4. Adaptation	3	3	3	3	2/2
	Overall Reflection Phase	3	3	3	3	
Overall SRL support		2.3	2.36	2.3	2.47	24/30

Several limitations of this study warrant consideration. First, the relatively small number of participants must be acknowledged. Obtaining meaningful assessments from individuals not well-acquainted with the learning environment posed significant challenges. This limitation affected both the inclusion of more diverse learning environments for current participants and the possibility to increase the overall number of participants for the learning environment under consideration. In future, the objectivity could be even further improved by a blind rating or students' rating. However, that may bring new challenges. One of these challenges could be that the knowledge of learning environment is not profound enough, for example a developer of LE would know the features very well, but not their effects on students' learning. Second, our study incorporated exclusively an analysis of a single learning environment. To further increase the reliability of the assessment, a greater variety of LE should be assessed that represent different aspects of SRL including very low to no SRL support. Third, there may be a potential bias in our selection of experts for the validation analysis. Nevertheless, we made efforts to include a highly diverse group of interuniversity, international and interdisciplinary experts with established backgrounds in SRL related research and development practices.

6. DISCUSSION and CONCLUSION

With the increasing integration of advanced learning technologies in higher education, it has become evident that support for students' self-regulated learning is not a binary concept. Rather, it encompasses various levels of support. This recognition of diversity presents another challenge for both researchers and educators, complicating the comparison of different developments, the design of effective pedagogical frameworks, and the determination of the optimal level of self-regulated learning support for specific contexts. In response to this challenge, we have recently developed the Self-Regulated Learning Support (SRL-S) rubric, a tool designed to empirically assess the extent and depth of SRL-S within a learning environment. The purpose of this study was to establish the reliability and validity of the SRL-S rubric. We examined various aspects to determine the consistency of ratings, including intra-rater and inter-rater reliability, and assessed whether the rubric was well-designed in terms of criteria and performance levels to differentiate the various levels of SRL support in educational settings. The results of this study indicate that the SRL-S rubric is both reliable and valid, making it a valuable tool for educators and researchers in higher education.

The validity of the rubric is grounded in the alignment of its criteria and performance levels with the concept it aims to measure. It also takes into account the knowledge and technological developments in the field, which are of interest to a diverse group of interdisciplinary experts focused on SRL support (Jonsson & Svingby, 2007). To ensure its validity, we consulted an international and interdisciplinary panel of experts who conducted qualitative content, construct, and criterion assessments of the rubric criteria and performance levels. Their feedback helped us clarify and refine the rubric's performance levels and align the terminology with the broader research community interested in SRL. Fortunately, no major issues were reported. Regarding the rubric's reliability, we employed interrater and intrarater reliability analyses. Interrater reliability proved to be good, while intrarater reliability demonstrated a moderate to almost perfect agreement between repeated ratings. These findings confirm that the rubric is a reliable instrument, delivering consistent results when used by multiple raters or when used multiple times with some time interval.

Future research endeavors should consider exploring the applicability of the SRS-S across diverse populations beyond Germany and especially in various educational settings, distinct from higher education delivered at a distance. This reliability exploration could expand the scope and utility of this tool. Second, subsequent theoretical and empirical research could further extend the rubric by incorporating students' usage indicators column. Existing research has shown that the mere availability of a technological tool in a learning environment does not guarantee its usage by students (Radović et al., 2024a; 2024b). Moreover, studies have demonstrated that the same learning technology can yield different learning outcomes and lead to different learning processes based on how students employ it (Radović, 2024). Consequently, the SRL-S rubric could serve as a valuable platform for comprehending whether and to what extent students utilize the available SRL support within the learning environment.

Ultimately, the SRL-S rubric can function as an instrument for conducting meta-analyses of literature reviews and empirical studies exploring learning environments published on the topic of SRL. Such research endeavors could contribute significantly to our understanding of optimal SRL support, the relationship between various levels of self-regulation and student success, as well as factors like anxiety, time pressure, and cognitive load. Presently, it is widely believed that more advanced SRL support leads to improved learning outcomes; however, extensive and rigorous empirical evidence to substantiate this claim remains lacking (Jivet et al., 2017). It has also become clear that a one-size-fits-all approach to teaching is inadequate, so finding right levels of SRL support for different educational contexts, educational disciplines, or domain-specific learning processes might also be promising ways for further research (Molenaar et al., 2023). To achieve this aim, this rubric could serve as the missing evaluation method and establish a foundation for better understanding.

Acknowledgments

This work was funded by the Center of Advanced Technology for Assisted Learning and Predictive Analytics (CATALPA) of the FernUniversität in Hagen. We would like to especially thank Ioana Jivet, Henrik Bellhäuser, Dennis Menze, Joerg M. Haake, and other colleagues for their feedback and support we have received in the process of rubric making.

Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the authors.

Contribution of Authors

Slaviša Radović: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing. **Niels Seidel:** Writing - Review & Editing, Project administration.

Orcid

Slaviša Radović https://orcid.org/0000-0001-8840-6053
Niels Seidel https://orcid.org/0000-0003-1209-5038

REFERENCES

Ameloot, E., Rotsaert, T., Ameloot, T., Rienties, B., & Schellens, T. (2024). Supporting students' basic psychological needs and satisfaction in a blended learning environment through learning analytics. *Computers & Education*, *209*, 104949.

American Educational Research Association. (2014). Standards for educational and psychological testing (AERA, APA, and NCME). Washington, USA: American Educational Research Association, ISBN 978-0-935302-35-6. Andrade, H., & Du, Y. (2007). Student responses to criteria-referenced self-assessment. *Assessment & Evaluation in Higher Education, 32*(2), 159–181.

Araka, E., Maina, E., Gitonga, R., & Oboko, R. (2020). Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018). *Research and Practice in Technology Enhanced Learning*, *15*(1).

Ceron, J., Baldiris, S., Quintero, J., Garcia, R.R., Saldarriaga, G.L.V., Graf, S., & De La Fuente Valentin, L. (2021). *Self-Regulated Learning in Massive Online Open Courses: A State-of-the-Art Review*. IEEE Access, 9, 511–528.

Devolder, A., Van Braak, J., & Tondeur, J. (2012). Supporting self-regulated learning in computer-based learning environments: systematic review of effects of scaffolding in the domain of science education. *Journal of Computer Assisted Learning*, *28*(6), 557–573.

Dong, X., Yuan, H., Xue, H., Li, Y., Jia, L., Chen, J., Shi, Y., & Zhang, X. (2024). Factors influencing college students' self-regulated learning in online learning environment: A systematic review. *Nurse Education Today*, *133*, 106071.

Edisherashvili, N., Saks, K., Pedaste, M., & Leijen, Ä. (2022). Supporting Self-Regulated Learning in Distance Learning Contexts at Higher Education Level: Systematic Literature Review. *Front. Psychol.*, *12*, 792422.

Gambo, Y., & Shakir, M.Z. (2021). Review on self-regulated learning in smart learning environment. *Smart Learning Environments*, *8*(1), 12. https://doi.org/10.1186/s40561-021-00157-8

Garcia, R., Falkner, K., & Vivian, R. (2018). Systematic literature review: Self-Regulated Learning strategies using e-learning tools for Computer Science. *Computers & Education*, *123*, 150–163.

Goda, Y., Yamada, M., Matsuda, T., Kato, H., Saito, Y., & Miyagawa, H. (2022). From Adaptive Learning Support to Fading Out Support for Effective Self-Regulated Online Learning. *Research Anthology on Remote Teaching and Learning and the Future of Online Education*, *254*–274.

Harris, J., Grandgenett, N., & Hofer, M. (2010). *Testing a TPACK-Based Technology Integration Assessment Rubric*. In D. Gibson & B. Dodge (Eds.), Proceedings of Society for Information Technology & Teacher Education International Conference 2010 (pp. 3833-3840). Chesapeake, VA: AACE

Heikkinen, S., Saqr, M., Malmberg. J., & Tedre, M. (2022). Supporting self-regulated learning with learning analytics interventions – a systematic literature review. *Education and Information Technologies, 28*, 3059–3088. https://doi.org/10.1007/s10639-022-11281-4

Järvelä, S., Nguyen, A., & Molenaar, I. (2023). Advancing SRL research with artificial intelligence. Computers in Human Behavior, 147, 107847.

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). *Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice*. In European conference on technology enhanced learning (pp. 82-96). Springer, Cham.

Jonsson, A., & Svingby, G. (2007). The use of scoring rubrics: Reliability, validity and educational consequences. *Educational Research Review, 2*(2), 130 144.

Lodge, J.M., & Harrison, W.J. (2019). The Role of Attention in Learning in the Digital Age. *The Yale Journal of Biology and Medicine, 92*(1), 21–28.

Matcha, W., Uzir, N. A., Gašević, D., & Pardo. A. (2020). A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. *IEEE Transactions on Learning Technologies*, *13*(2), 226-245.

McGraw, K.O., & Wong, S.P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological Methods, 1*(1), 30–46.

Mirriahi, N., Joksimović, S., Gašević, D., et al. (2018). Effects of instructional conditions and experience on student reflection: A video annotation study. *Higher Education Research and Development, 37*(6), 1245–59

Molenaar, I., Mooij, S.D., Azevedo, R., Bannert, M., Järvelä, S., & Gašević, D. (2023). Measuring self-regulated learning and the role of AI: Five years of research using multimodal multichannel data. *Computers in Human Behavior, 139*, 107540.

Moskal, M., & Leydens, J. (2019). Scoring Rubric Development: Validity and Reliability. *Practical Assessment, Research, and Evaluation, 7*, 10.

OECD (2019). *Getting skills right: Future-ready adult learning systems*. Paris: OECD Publishing.

Panadero, E. (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. *Front. Psychol*, *8*, 422.

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60*(6), 723–735.

Pérez-Álvarez, R., Maldonado-Mahauad, J., & Pérez-Sanagustín, M. (2018). *Tools to Support Self-Regulated Learning in Online Environments: Literature Review*. In Lecture notes in computer science (pp. 16–30).

Pintrich, P.R. (2000). *The role of goal orientation in self-regulated learning*. In M. Boekaerts, P.R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 451–502). Academic Press.

Radović, S. (2024). Is it only about technology? The interplay between educational technology, teaching practice, and students' learning activities. *Journal of Computers in Education, 11*, 743–762.

Radović, S., & Seidel, N. (2024a). Introducing the SRL-S rubric for evaluating technology-enhanced learning environments for self-regulated learning. Accepted for publication in *Innovative Higher Education Journal*.

Radović, S., & Siedel, N. (2024b). *Bridging learning science and learning analytics: Self-Regulation Learning support (SRL-S) rubric*. 14th International Conference on Learning Analytics & Knowledge (LAK24). 18. – 22. 3. 2024, Kyoto, Japan.

Radović, S., Seidel, N., Haake, J.M., & Kasakowskij, R. (2024a). Analyzing students' self-assessment practice in a distance education environment: Student behavior, accuracy, and task-related characteristics. *Journal of Computer Assisted Learning, 40*(2), 654–666.

Radović, S., Seidel, N., Menze, D., & Kasakowskij, R. (2024b). Investigating the effects of different levels of students' regulation support on learning process and outcome: In search of the optimal level of support for self-regulated learning. *Computers & Education*, *215*, 105041.

Reddy, M., & Andrade, H. (2010). A review of rubric use in higher education. *Assessment & Evaluation in Higher Education, 35*(4), 435-448.

Sghir, N., Adadi, A., & Lahmer, M. (2022). Recent advances in Predictive Learning Analytics: A decade systematic review (2012–2022). *Education and Information Technologies, 28*(7), 8299–8333.

Thaler, N., Kazemi, E., & Huscher, C. (2009). Developing a rubric to assess student learning outcomes using a class assignment. *Teaching of Psychology*, *36*(2), 113–116.

Viberg, O., Khalil, M., & Baars, M. (2020). *Self-regulated learning and learning analytics in online learning environments*. In Proceedings of the 10th International Conference on Learning Analytics Knowledge (LAK'20). ACM, New York, NY, USA, 11 pages.

Wang, S., Christensen, C., Cui, W., Tong, R., Yarnall, L., Shear, L., & Feng, M. (2023). When adaptive learning is effective learning: comparison of an adaptive learning system to teacher-led instruction. *Interactive Learning Environments*, *31*(2), 793–803.

Wu, T.T., Lee, H.Y., Li, P.H., Huang, C.N., & Huang, Y.M. (2023). Promoting Self-Regulation Progress and Knowledge Construction in Blended Learning via ChatGPT-Based Learning Aid. *Journal of Educational Computing Research, 61*(8), 3–31.

Zimmerman, B.J. (2000). *Attaining self-regulation: a social cognitive perspective*. In Handbook of Self-Regulation, eds M. Boekaerts, P.R. Pintrich, and M. Zeidner (San Diego, CA: Academic Press), 13–40. Altman, D.G. (1999). Practical statistics for medical research. New York, NY: Chapman & Hall/CRC Press.

APPENDIX

Appendix A. The SRL-S rubric - assessing the extent of SRL support within a learning environment

SRL		Limited SRL support (1)	Moderate SRL support (2)	Advanced SRL support (3)
Forethought Phase	*F1. Goal Setting*	LE provides goals predefined by the teacher, and do not allow students to set or modify their goals within LE, nor can they easily access goal related performance indicators.	LE offers detailed insights into students' learning progress in relation to the course goals. However, it does not allow students to set or modify their own learning goals within the platform.	LE offers a variety of learning goals for students to choose from (e.g. course mastery or passing). Students can also set custom goals related to content or performance. Also, LE provides detailed analysis related to the chosen goals.
	F2. Strategic Planning	LE facilitates the sharing and accessibility of learning resources but does not include tools to help students select learning paths, determine appropriate actions, or plan task execution.	LE provides with an overview of all available learning resources (those completed, left unfinished, or which are next), allowing them to quickly access, prioritize tasks and identify the materials they need.	LE provides students with an overview of all available learning resources, along with useful information such as success rates, progress tracking, and estimated time required for each resource.
	F3. Self-Efficacy and Outcome Expectation	LE provides minimal information, typically at midterm, about students' past performance, such as their success, progress, effort, or time spent. It does not actively promote the development of self-efficacy.	LE offers detailed information about students' performance, progress, and effort, while also prompting them to reflect on their self-perceived efficacy and assess their capabilities.	LE provides students with details about their efficacy or prompts them to reflect on their self-perceived efficacy. LE goes a step further by offering predictions (about success, outcomes, time needed, etc.) and help to set realistic expectations.
	F4. Task Value and Interest	LE provides assignments with no or limited practical application, connection to next learning chapters, or other subject or courses.	LE allows students to apply their knowledge to solve realistic practice assignments (follows the principles of authenticity).	LE provides advanced learning technologies that allows students to use professional tools, skills, or relevant methods (for their study or selected goal) to create or self-assess knowledge.
	F5. Goal Orientation	LE provides only general information regarding the course requirements (goal set by teacher). Students lack visibility into how they are performing or advancing towards their goals.	LE offers students' detailed criteria for success and displays their performance in relation to the goal (set by teacher). Students can compare progress and performance against the criteria and their goal.	LE goes beyond providing information about students' progress, process, and outcome in relation to their goals. It also visualizes what and how needs to be improved or adjusted to attain the selected goal.
Performance Phase	*P1. Self-Instruction*	LE provides outline and table of learning content. Besides, there are general instructions about the course requirements to helps individuals take control of their learning.	LE provides task-specific or general self-questions along learning resources to prompt students to achieve desired outcomes.	LE provides adaptive cues that directed cognitive process and thinking during learning. A technology (like intelligent chatbot or similar) uses motivational technique to instruct steps in the coping process.

	P2. Imagery	LE uses images and visual representation of learning material to support the forming of vivid mental pictures and visual models.	LE includes videos and tools for graphical strategies within the text (annotations, color-coded text, and similar visual aids are utilized to enhance knowledge organization).	LE provides interactive simulations or virtual reality space for developing knowledge and practicing skills. LE could also support students in creating concept maps and visualizations.
	P3. Time Management	LE provides limited support for time management e.g., only mentioning deadlines and exam dates. LE do not record nor analyze time spent on learning.	LE provides information about students' past performance as well as the time spent on specific learning resources and overall learning. Deadlines reminders could be sent.	LE provides information about students' past behavior (or success, progress, time, etc.), but also offers future predictions on managing time effectively in relation to their selected goals.
	P4. Help Seeking	LE facilitates scheduled communication with the teacher. However, it lacks clear avenues or guidance for students to seek assistance when encountering challenges.	LE offers a/synch channels for communication (forum, chat, LMS tools, etc.) which students can use to engage with peers and teachers, to ask questions, share concerns, or request support.	LE instructs and supports students to use various communication channels (e.g., tasks shared with peers, collaborative joint activities). Additionally, help seeking support includes external resources, AI agents, or querying LLM.
	P5. Task Strategies	LE provides a general description of different strategies that can be used. There is no specific structure to support students in performing different tasks.	LE offers task-related support strategies during learning activities (e.g. solving tasks, or self-assessing task solutions). Students are supported in redoing tasks using alternative strategies.	LE offers task-specific strategies for different tasks (this can include tips on critical thinking, summarization, application of skills). Moreover, LE provide feedback on students' learning strategies, behavior, and effective strategies etc.
	P6. Metacognitive Monitoring	LE do not specifically support analytics, monitoring understanding, and evaluating success of chosen learning strategies; aside from providing knowledge tests and tasks that require manually scoring results.	LE supports students in monitoring their progress in relation to general course outcomes. Students can gauge their overall performance (or success, progress, etc.) against the formal objectives of the course (usually via learning dashboards).	LE enables students to compare their progress globally, but also in relation to learning units, specific materials (e.g., texts, tasks, reflections), and individual items. Additionally, LE provides monitoring of SRL behavior, used strategies, and learning patterns.
Self- Reflection Phase	***S1. Self-Evaluation***	LE provides a sample solution that may help students to self-evaluate their solution against master solution (feed-up). However, it does not support identification of areas for improvement.	LE provides different types of tasks that allow students to evaluate their knowledge and skills through, for example, various assessments, self-assessments, or quizzes (feed-back).	LE provides tasks for self-evaluation, but also offers additional data analysis, feedback and guidance on specific areas that need attention (feed-forward). LE marks and visualizes tasks that are underperformed in relation to the goal, recommending improvement.
	S2. Causal Attribution	LE offers a limited resources to reflect (e.g., knowledge tests and related rubrics). No questions specifically guide students how to evaluate factors of failure.	LE encourages students to consider factors that influenced their failures. For example, self-assessment tasks involve rating solutions against different criteria or master solution.	LE includes prompted critical reflection tasks after significant learning events or units. These tasks encourage reflection on strengths and weaknesses, performance, and progress toward achieving goals

	S3. Self-Reactions	LE includes knowledge assessments with corresponding rubrics, but it does not consider experiences, emotions, or future goals.	LE incorporates learning dashboard that provide insights (awareness and reflection) on their learning activities.	LE provide a learning dashboard together with critical reflection tasks that specifically ask students to reflect on their learning experiences or think about their feelings of satisfaction or disappointment.
	S4. Adaptation	LE provides limited guidance or resources to assist students in modifying or adapting their approaches to learning. This is usually organized as scheduled virtual cohort meetings with teachers.	LE provides information about learning progress and outcome. However, learning material do not adapt, and students cannot directly modify their learning goals within the LE.	LE includes critical reflection tasks that specifically ask students to reflect on adjusting their learning strategies, setting new goal within LE, and to adapt their strategies (based on the information about learning progress).

Note: *As introduced in Radović and Seidel (2024a). Assign performance levels to each criterion. The corresponding rating (1, 2, or 3) can be assigned only if all requirements from the level are fulfilled. Otherwise, a lower rating should be given (except for when "limited" level has not been reached, then 0 should be given*