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A Systematic Literature Review of Self-regulated Learning and Artificial Intelligence in Higher Education

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Research highlights a pressing need for conceptualizing Self-Regulated Learning (SRL) in modern higher education, particularly in the context of Artificial Intelligence (AI). We systematically review studies on SRL and AI in higher education. A total of 934 articles were found on the Web of Science or WoS (877) and Scopus (57) and assessed using PRISMA protocol. A total of 14 studies were included in this review. The systematic review seeks to examine and synthesize: aspects of SRL that have been studied at the intersection of AI and SRL, limitations reported by the studies at the intersection of AI and SRL, and considerations for a new model of SRL in light of AI. Findings reveal diverse theories and technologies used and attributed to SRL building with AI in higher education literature. Such diversity can lead to a lack of a universal outlook and generalizable findings. The discussion highlights avenues for future research and proposes methodological approaches for studying SRL in AI-enabled learning environments. This work contributes to a set of practices and tools to better conceptualize SRL with AI.

Keywords: Self-Regulated Learning (SRL), Higher Education, Artificial Intelligence (AI), Learning Environments

Introduction

This systematic literature review paper explores the intersection of Self-Regulated Learning (SRL) and Artificial Intelligence (AI) enabled learning environments in higher education to identify best practices and strategies that instructional designers and students can employ during teaching and learning. Self-regulated learning supports learning development using various thinking skills that are higher-level and rely on students' 1) forethought, 2) performance, and 3) self-reflection (Zimmerman 2002).

Self-Regulated Learning or SRL

Various models and frameworks of SRL exist in the literature (Bjork et al., 2013; Dinsmore et al., 2008). Often, SRL considers three key phases that can better facilitate student learning. Students may iteratively 1) plan for an educational task, 2) execute and monitor the task, and then 3) reflect on their approach (Zimmerman & Schunk, 2011). Doing so helps students become more in charge, understand the requirements for completing a given task, and adjust this learning process based on their needs and abilities. Self-regulated learning suggests that successful students set goals for their education or achievement and choose from a diverse array of strategies to reach their goals (Winne, 1995; Zimmerman, 1990). Hence, successful students have a good measure of their abilities and can evaluate their strengths and weaknesses in planning and executing a given academic task. Our goal in this work is not to prescribe what SRL is, but rather to acknowledge that it is a fluid concept that, at its core, aims to support students' active and reflective participation in the academic task(s).

Artificial Intelligence or AI-Enabled Learning Environments

AI-enabled learning environments may span a large space in the design, delivery, and administration of teaching and learning experiences (Cope et al., 2021). Students, for example, may enter a classroom with a didactic setting and think this is a traditional course when in reality the instructor has used AI in the design of the course or for the assessment process. Pedagogy that uses AI in any part of its design, delivery, administration, and outcomes may thus be considered an AI-enabled learning environment (Machicao 2022). AI-enabled learning environments offer task delegation, big

data collection, computation, natural language processing, and much more in designing, responding to, and evaluating an academic task normally carried out with human instructors, students, and assessors (Kabudi et al., 2021). It is likely that, an AI-enabled learning environment may offer both potential and threats to student learning and academic integrity (UNESCO 2023).

Gap and Development of the SRL Model with AI in Higher Education

With AI becoming tangled with everyday pedagogy in higher education, it is becoming clear that a ban culture is ineffective and may fuel academic misconduct in more elusive ways (Harrison, Hurd, and Brinegar 2023). As such, we find it necessary to accept and analyze the role AI can play in learners' self-regulation more formally. There is a lack of reviews on the intersection of SRL and AI learning environments. Recently, studies have been conducted to analyze AI's role in students' SRL (Lim et al., 2023; Molenaar et al., 2022; Xia et al., 2023) Predominantly through the use of multiple data sets and learning analytics. The multimodal analysis argues that data collected from a single modality may present less insight than from multiple modalities. Various modalities of erroneous data (e.g., noise or data not signifying SRL) will not differ much from a single modality of erroneous data. The increased attention to multimodal data and the lack of pedagogical grounding for AI surrounding SRL urge more work on this topic.

The focus of this paper is twofold: First, we conduct a systematic literature review of past studies at the intersection of AI and SRL in higher education. This review summarizes the types of studies conducted on this topic. Second, and via the synthesis of the reviewed studies, we analyze the reported challenges and potentials of the proposed studies and use them to inform what may or may not work for SRL and AI in higher education. Our research questions are:

- RQ1: What aspects of SRL have been studied at the intersection of AI and SRL?
- RQ2: What limitations have been reported by the studies at the intersection of AI and SRL?
- RQ3: What are the considerations for a new SRL model in light of AI?

Background

This section provides background information on factors influencing SRL and key SRL models. Doing so enables us to pinpoint the gap in the literature, namely, a lack of systematic review of SRL models in AI-enabled learning environments.

Factors Influencing SRL

Because SRL is a broad concept, various factors that influence it have been noted across the literature. In cognitive and educational psychology, for example, techniques (Figure 1) have been shown to contribute to students' SRL (Dunlosky et al., 2013):

Figure 1
Techniques contributing to students' SRL (Dunlosky et al., 2013)

1. Laboratory interrogation deals with justifying whether a fact or concept is true.
2. Self-explanation involves connecting newly acquired information with what was known before or sharing problem-solving steps.
3. Summarization deals with drafting an abstract of key ideas of various lengths for learning.
4. Highlighting/underlining deals with extracting key pieces of information.
5. Keyword mnemonic deals with techniques such as keywords and imagery for verbal information.
6. Imagery for text involves creating mental schemas and images during listening or reading.
7. Rereading deals with reviewing material after the first time read.
8. Practice testing deals with going over practice tests to improve learning.
9. Distributed practice deals with scheduling and planning study time and approach.
10. Interleaved practice deals with mixing different problem types when scheduling for learning.

While the abovementioned and other techniques may increase the chances of self-regulation, it is still largely upon the student to understand self-regulated strategies and influencers appropriately. For example, a meta-analytic review by Panadero et al. explored the effects of self-assessment on the students' SRL and self-efficacy (Panadero et al., 2017). They found self-assessment strategies and demographics, such as gender, impacted SRL.

The presence of learning analytics opens the opportunity to analyze SRL through more measurable means and identify what factors are significant. For example, it has been seen that blended and online learners do not differ significantly

in their SRL predictors of academic performance (Broadbent 2017). Yet we should also caution that learning in MOOCs alone cannot be fully understood by learning analytics and requires an understanding of individual learners ' work by Littlejohn et al. (2016) confirms the need to understand and theorize SRL in new technologically enhanced settings.

Based on the characteristics of prominent SRL models studied, pedagogically, SRL requires:

- activation of goal setting, performance, and reflection,
- critical thinking and metacognitive thinking to improve their SRL strategies,
- regulation of own learning efforts along with psycho-social factors such as motivation, collaboration
- understanding the constraints and requirements of the environment in which they exert and exercise SRL, which may include computer-assisted and more recently AI-enabled learning environments.

Methods

Our goal with the systematic search process is to offer insight into what work has been done to facilitate and strengthen SRL in AI-enabled learning environments.

Search Process

An overview of the screening criteria can be found in Table 1, and the search process can be found in the PRISMA chart in Figure 2. The Web of Science (WOS) and Scopus were used to search for articles. We included articles published in international peer-reviewed journals and conference proceedings. Our search included publications written in English during an unlimited time frame. The following string was searched in the mentioned databases: (ai OR artificial intelligence) AND (self-reg* OR self reg*) AND higher education. We employed the OR operand to include both accepted notations of terms and further used * to include multiple derivations of the SRL term, such as self-regulated, self-regulation, and so on. Inclusion criteria included studies that reported AI and SRL in their title and/or abstract in higher education and English for an unlimited time frame. Studies that did not include our key terms of interest, were not in English, or focused on a healthcare domain, secondary, or non-higher education setting were omitted from this review.

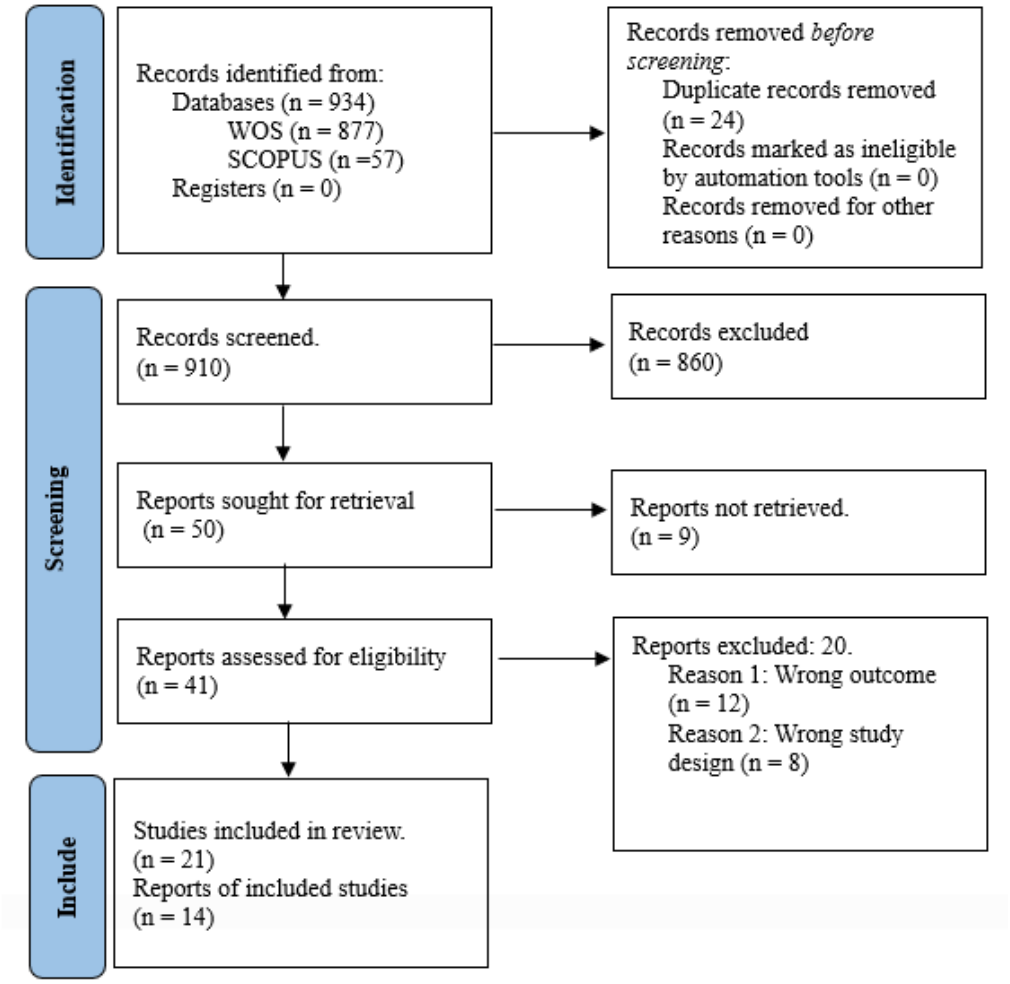
Table 1
Inclusion and Exclusion Criteria

Inclusion criteria	**Exclusion criteria**
Journal article and conference	Book reviews or studies regarding public policy
Studies shared in English	Studies not shared in English
Higher education foci	Studies not on higher education

A total of 934 articles were found on the Web of Science or WoS (877) and Scopus (57). Of these, 24 were duplicates and removed, leading to 910 records screened. A total of 860 studies were excluded as they predominantly explored SRL in a healthcare context. Of the 50 remaining studies sought for retrieval, nine could not be retrieved, leading to 41 reports assessed for eligibility. Further, 20 papers were excluded due to having either a wrong outcome (12) or a study design (8). A total of 21 studies were assessed for eligibility, and 14 studies were included in this review.

Of the reviewed 14 studies, the USA had the highest publications, followed by the UK, China, and Saudi Arabia. Comparatively, the USA had a higher number of independent publications, whereas most other countries had international and multinational collaborations.

Figure 2
PRISMA chart



Data Analysis

Our systematic search protocol includes:

- Input the noted search string in both SCOPUS and WoS.
- Download the paper records (full) and add them to Covidence. Covidence is a software used for Screening and data extraction (Covidence 2023).
- Covidence identifies duplicate studies.
- Remove duplicate studies.
- Conduct a title and abstract review of each article for inclusion or exclusion.
- Download and review the full text of each article for inclusion or exclusion.
- Extract and chart types of studies from articles in Excel.
- Synthesize a full review of each article and share future recommendations and challenges in the discussion section.

Results

This section shares a summary of the literature review findings about our research questions.

RQ1: What aspects of SRL have been studied at the intersection of AI and SRL?

There were seven quantitative studies, five mixed-methods studies, and two review papers. An overview of the theory and technologies noted in each reviewed research is presented in Table 2 and described next.

Table 2
Overview of SRL theory employed in the reviewed studies

Theory	Technology	Reference
Crowder's theory plus adaptive self-assessment feedback	Early recognition system and machine learning	(Ciolacu et al. 2019)
Adaptive tutoring, social robots in education, and the author's prior work	The Pepper adaptive robotic tutor	(Donnermann et al. 2022)
Eisenhower principle	Education 4.0 technologies (e.g., adaptivity, mobile connectivity, personalization)	(Haderer and Ciolacu 2022)
Artificial Intelligence Framework for SRL (AIF-SRL)	Self-Regulatory Efficacy (SRE)	(Huang et al. 2022)
Flow theory	Meta learner (MTL)	(Jebur, Al-Samarraie, and Alzahrani 2022)
Pedagogical SRL strategy	Information Technology (IT)	(Liu et al. 2022)
Collaborative Knowledge Construction (CKC) at cognitive and regulative behavior dimensions	Integrated analytics approach (Hidden Markov Model combined with Lag sequential analysis and Frequent sequence mining)	(Ouyang et al. 2023)
Student agency	The intelligent game-based learning environment for microbiology, Crystal Island	(Sawyer et al. 2017)
Mental model shifts	Hypermedia environment	(Sullins et al. 2007)
Hattie and Timperley's effective feedback model	Personalized and analytics feedback	(Suraworachet, Zhou, and Cukurova 2023)
Winne and Hadwin's information processing theory of SRL	Hypermedia-based intelligent tutoring system: MetaTutor	(Taub and Azevedo 2019)
VARK model of learning styles	Adaptive e-learning environments	(Vemuri, Snoeck, and Poelmans 2021)
Personal and educational goals	SIDDATA data-driven digital study assistant	(Weber et al. 2022)
Zimmerman	Python 3.8 programming algorithm, agglomerative hierarchical clustering, lag sequence analysis, SPSS 21.0	(Ye et al. 2022)

Ciolacu et al. (2019) presented an early recognition system with machine learning to inform at-risk students halfway through the semester. The authors present an AI-assisted higher education process with smart sensors and wearable devices for SRL. Their system follows Crowder's theory with adaptive self-assessment feedback. In this view, learning does not result from the correct response but from the realignment of the learner.

Donnermann et al. (2022) compared the effect of an adaptive tutor to a control condition over three sessions during one semester. They used an adaptive robot called Pepper and utilized theory from research on adaptive tutoring, social robots in education, and the author's prior work in this field. The authors found that subjective knowledge and intrinsic motivation increased. However, the extended adaptability was not able to significantly improve learning as compared to the non-adaptive version of the robot.

Haderer and Ciolacu (2022) propose that artificial Intelligence-assisted SRL is intended to deliver independent learning opportunities for students. Learning arises via tutoring, hints, and precise feedback. The authors presented an AI-

assisted task and time planning system and its architecture. They adapted the Eisenhower principle to sort students' learning tasks according to the two dimensions of importance and urgency.

Huang et al. (2022) propose an Artificial Intelligence Framework for SRL (AIF-SRL) which offers students tutoring, hints, and precision feedback, and aims to identify at-risk students. They adapted the theory of self-regulatory efficacy from cognitive psychology. The authors considered several dimensions of SRL, such as multiple intelligences, academic performance, self-concept, and intrinsic motivation. The results of their analysis showed that SRL influences satisfaction and academic performance. They propose a four-step model of SRL that is intertwined with AI as follows:

1. Planning: goal setting, enabling, time management, help-seeking
2. Preparing: enabling, help-seeking
3. Learning: elaborating, rehearsing, organizing, self-monitoring
4. Reflecting: goal setting

Jebur et al. (2022) integrated the concept of flow into a Meta learner (MTL) design to help reduce anxiety and increase self-regulation among students. The flow theory was developed by Csikszentmihalyi (1975). In this view, learners can experience optimal learning when they perform tasks characterized by a skills-challenge balance and a person's interest, control, and intense focus. Authors found that generally incorporating flow into the design of MTL can help reduce anxiety and improve self-regulation.

Liu et al. (2022) implemented an online homework intelligent platform was implemented by information technology, or online homework assignments were used to strengthen four components of the SRL strategy, i.e., self-disciplinary control, independent thinking, reflective learning, and interest development. More specifically, the platform can help:

- Allow students to solve problems on their own by facilitating more avenues for learning online.
- Provide the students with the same questions, but tweak the different known conditions.
- Examine student learning through data collected from procedures students participated in answering the questions.
- Create learning communities where the achievements of students and faculty are shared.

The three-year implementation and revision of this platform since COVID-19 shows promising results in facilitating students' SRL in online settings. Ouyang et al. (2023) examined the contribution of individual group members to learning through their interaction and information sharing. The findings of testing the approach suggest that in the peers' consensus-building process, the peer-level and group-level regulations had an important role to play as mediators in facilitating students' cognitive communication,

Sawyer et al. (2017) examined the impact of student agency on learning and problem-solving behavior in a game-based learning environment called Crystal Island. Three versions of the system were presented, namely high, low, and no agency conditions. Each student only interacted with one version of the system. The agency was manifested in the level of control students had in navigating and making decisions in an open (i.e., high agency) versus prescribed (i.e., low agency) and closed (i.e., no agency) way. Results of their analysis showed low agency to serve students better than the high and no agency conditions.

Sullins et al. (2007) examined shifts in students' mental models when using a hypermedia environment to share everything they know about the circulatory system. The SRL processes were categorized as "planning (e.g., prior knowledge activation, recycle goal in working memory), monitoring (e.g., content evaluation, the feeling of knowing), strategy (e.g., coordinating informational sources, drawing), task difficulty and demand (e.g., help-seeking behavior, task difficulty), interest (e.g., interest statement), or feedback (positive or negative)" (p. 4). According to the chi-square analyses, it is only after a question is generated that high shifters are showing a higher degree of metacognitive monitoring (i.e., the judgment of learning, the feeling of knowing).

Suraworachet et al. (2023) analyze a personalized behavioral feedback intervention based on students' writing engagement analytics by using a time-series analysis of digital traces from a ubiquitous online word-processing platform. They follow the feedback theory from Hattie and Timperley (2007) which focuses on the type and delivery of feedback. Findings presented statistically significant improvements for the group, especially for students with low SRL competence, who received combined human and learning analytics feedback as compared to human feedback only.

Taub and Azevedo (2019) use eye tracking and log-file data to analyze fixations and self-regulated areas of interest when working with MetaTutor, an intelligent Tutoring system that teaches students about the human circulatory

system. The authors demonstrate that multichannel process data can be used to assess how students engage in SRL, where SRL is a series of events that unfold over time. The authors find it important to pinpoint students' learning characteristics, such as prior knowledge, to facilitate appropriate prompting.

Vemuri et al. (2021) propose an adaptive e-learning environment based on students' learning styles. A student engagement scale is used to measure the following affective and behavioral factors of engagement (skills, participation/interaction, performance, and emotional).

The authors follow the VARK model (Fleming and Baume, 2006) which represents:

- Visual
- Auditory
- Read/write.
- Kinesthetic

A significant difference in learning outcomes, as well as positive results for adaptive e-learning students, was found. Further, results suggested that students' learning styles are unique, and they have diverse preferences for the use of instructional material and activities.

Weber et al. (2022) present the SIDDATA software architecture, design philosophy, and modular, feature-centered application logic. A system architecture and feature explanation of the system is provided. Ye et al. (2022) followed Zimmerman (2002) and machine learning algorithms to differentiate between student groups. The lag sequence analysis method, for example, can help explain the learning behavior path of learners at different levels and the mechanism of the generation of learning patterns to activate improved SRL in students.

RQ2: What limitations have been reported by the studies at the intersection of AI and SRL?

Analysis of limitations reported by the reviewed studies presents more work needed to both understand and predict SRL behaviors in intelligent AI-enabled learning environments.

Ciolacu et al. (2019) suggest the need for the aggregation and use of more sensors, such as biological signals, to improve study gain and accuracy. Such a need requires both appropriate use and data collection and derivation of data. Donnermann et al. (2022) also propose the need for more fine-grained field studies, though their method of data collection is not necessarily through biological data. The authors find that more in-depth field studies can help gain more insight into possible applications of robotic tutors in higher education.

Haderer and Ciolacu (2022) find work to remain with digitalization and increase both the integrity and efficiency of teaching and learning experiences. The authors provide click instances as an example that can add or remove the burden on the learner based on the user interface design. Huang et al. (2022) share the difficulty of monitoring SRL strategies and behaviors, such as satisfaction and academic performance, in real time.

Jebur et al. (2022) inform that future work can explore how other flow antecedents may contribute to the learning experience of students. The learning task in this study was limited to essay-type and multiple-choice questions and thus not generalizable to other domains. Similarly, Liu et al. (2022) found the need to expand on the homework available on their platform to explain choice, fill-in-the-blank, and programming questions. Suraworachet et al. (2023) highlight the need for investigating the longevity of impacts and their cross-context validity in intelligent feedback environments. Taub and Azevedo (2019) note the need for validity and reliability measures of pre and post-tests.

Ouyang et al. (2023) suggest including dimensions such as socio-emotional engagement, such as the collection and analysis of multimodal data on students' socio-emotional states. They further encourage testing on a larger scale and across more diverse contexts. In a similar vein, Sawyer et al. (2017) endorse the examination of the motivational impact of varying student agencies. Sullins et al. (2007) promote the development of cognitive disequilibrium, followed by questioning of the student from the intelligent tutoring system in real-time to help regulate their SRL.

Several challenges with measuring or developing SRL in light of AI technologies are presented. Vemuri et al. (2021) point out the mixed findings regarding the efficacy of adapting teaching to learning styles. Weber et al. (2022) reveal the difficulty of balancing personal data protection with the usage of data for scientific purposes. Ye et al. (2022) share limitations in coding, classification, analysis, and in-depth understanding of SRL behaviors and patterns of student groups. The authors point out the limitation of students' SRL building outside the system and the lack of protocols to measure and track such developments.

RQ3 What are the considerations for a new model of SRL considering AI?

In the sections that follow, we aim to combine the traditional and technology-enhanced perspectives and offer media in which a new model of SRL in AI can be conceptualized. Note that the proposed approaches do not theorize or assert relationships, but rather provide frameworks to better study and characterize SRL in AI settings.

Conceptualizing SRL considering AI. Findings of the review indicate there are differences in conducting effective self-regulation and learning. Effective self-regulation may require mechanisms for the learner to be able to drive motivation for learning, effective self-monitoring for learning, normalizing evaluation of the self (e.g., not under- or overestimating), and pursuing topics of interest for learning and revision.

1. Self-regulation can take on three levels, namely the learner only, the learner with AI as a coach, and AI only as the sole self-regulator. At the
   A. learner level, the student is responsible for their self-regulation, or strategizing and activating mechanisms to facilitate learning.
   B. learner and AI level, both the student and AI communicate with one another in a bidirectional manner, and are responsible for the learner's self-regulation.
   C. AI level, only the AI in a one-directional manner, is responsible for the learner's self-regulation.

2. Learning takes on two levels, namely the learner, or the learner, and AI as a coach. The third, that is, AI being the learner is inappropriate (unless AI becomes an augment of the human in the future) since we ultimately wish to see learning efforts and gain by the human learner. At the:
   A. learner level, the student is learning and is expected to fully grasp a concept or skill on their own.
   B. learner and AI level, learning is distributed between the learner and AI. A simple example is that the student is expected to use AI to make an integration from an n-order function, but is not expected to memorize or know how to take the integration themselves.

In this view, self-regulation may take on one of three forms, and learning may take on one of two terms simultaneously and change forms over time. The notion of SRL, therefore, happens at the intersection of these forms and requires attending to both who is carrying out the self-regulation part and how the student is achieving learning.

Conceptualizing probabilistic states of factors influencing SRL using AI. Much of the reviewed SRL literature emphasizes the complexity of this topic due to being related to many cognitive and behavioral factors, including but not limited to motivation, metacognition, emotion, demonstration of understanding, demonstration of skills, and so on (Balapumi et al., 2016; Virtanen et al., 2015). To date, we have not been successful in creating an exact metric and tool to measure SRL directly. We do not have a deterministic picture, so we may need to use technology such as AI to develop a probabilistic view of SRL. That is, we can only say what factors are probable to influence the SRL of students. We can attribute a probability to each factor and its likelihood of appearing in one of the three phases of SRL as suggested by Zimmerman. A probabilistic framework could assign likelihood estimates to key SRL factors across SRL phases (e.g., forethought, performance, reflection).

Conceptualizing SRL opportunities using AI. Personalized and multimodal features of AI may contribute to different phases and ways SRL can be understood and improved, namely:

1. Helping students become aware of the mechanisms of SRL. Examples include:
   - AI helps students understand what SRL entails and what it means, for example, to go through phases of forethought, behavior, and reflection.
   - AI helps students understand their social and psychological attributes (e.g., team-building skills, being introvert/extrovert, agreeable with feedback or not, being motivated or not) and how that may shape their SRL strategies.
2. Providing opportunities for students to put SRL to the test. Examples include:
   - AI suggests which learning activities are good opportunities for SRL development to the students before they begin,
   - AI making SRL prompts and reflection for students, augmented to learning activities (e.g., may not count towards the grade but provided to help students with their SRL).
3. Assessing and guiding students on ways to improve their SRL. Examples include:
   - AI tracking students' demonstrated and shared SRL strategies and output,
   - AI advises students on ways they can improve their SRL strategies.

Conceptualizing Social SRL Matrix. Every entity may or may not have social interactions with other entities in a learning environment. The entities may be individuals in a team, classroom, or even groups. Multimodal data may ultimately enable measuring and predicting an SRL score for each entity. The score may represent an aggregate

of demographics (e.g., ethnicity), psychological (e.g., motivation), and social (e.g., team-building skills) attributes. The idea is that an entity has an SRL score for itself, and such a score changes when interacting with other entities. The SRL social matrix may thus provide a structured way to study social interactions and examine how SRLs evolve across entities. Such matrices, when collected over time, can in turn help in predicting future social SRL gains of entities based on historic data and machine learning algorithms.

Conceptualizing SRL communication using AI. Once the individual and social SRL scores of entities are obtained, we need to communicate them to both teachers and students to inform them of the attributes of students and how they may impact their learning progress through the use of simple radar plots. We may show SRL as a function of motivation, emotion, and cognition (e.g., course-specific skills and knowledge), when AI programs may use multimodal data to derive an aggregate score for the three or more constructs. Learners may be more driven by cognition in their individualistic learning; their SRL score declines upon social interaction. Another learner, on the other hand, may be more driven by their emotions in their individualistic learning and their SRL score to improve upon social interaction. The area of each profile may provide the total SRL score.

Discussion

Quantitative and mixed methods studies were the most common type of studies among the reviewed articles. The review of the 14 articles helped us realize the diversity of theoretical frameworks, tools, contexts, data sets, types, durations, participants, analysis methods, and other factors that exist in the literature. Such differences can lead to a lack of a universal outlook and generalizable findings. The results helped us conceptualize avenues for future research to utilize and allow approaches to study SRL in AI. Yet, we find the following challenges to remain.

Conceptualizing the Self in SRL Using AI

One difficulty of conceptualizing SRL with any aid external to an entity is whether that help can be truly considered Self-regulated. Technology such as AI can provide support for individuals to improve their SRL, but an important implication of this is that the SRL is no longer moderated solely by the "self". As such, the use of technology such as AI in teaching and learning still bears complex societal and moral dilemmas and uncertainties. On the one hand, we wish to improve the efficiency and productivity of learning through any means possible, and on the other hand, we need to be careful of what students create a habit of relying on in the event that those support systems are taken away from the student.

Conceptualizing SRL from Single or Multiple Modalities

AI, more broadly, has little context and experience in how humans of diverse backgrounds behave and make decisions in light of hard-to-measure factors such as emotion, motivation, and so on. Unless we can boil down the entirety of being to a set of equations and discretized parameters, these findings suggest we still have quite a lot of work ahead to characterize humanistic decision-making, specifically considering subjective notions such as the soul, likes, dislikes, and so on.

Conceptualizing SRL in Closed vs. Open-ended Questions Using AI

The mechanisms to activate and sustain SRL may be different for closed to open-ended questions, with open-ended questions understandably being more complex. So, work done in AI should not attempt to trivialize learning by configuring open-ended problems as a set of closed-ended problems, but instead study each context with the entities separately.

Conclusion

This systematic literature review paper examines the intersection of Self-regulated Learning (SRL) and Artificial Intelligence (AI) learning environments in higher education to identify best practices and strategies that instructional designers and students can employ during teaching and learning. Findings indicate that quantitative and mixed methods are more prevalent when studying SRL with AI in higher education. Through the review of 14 studies and summarizing their reported approaches and limitations, we conceptualized avenues that future research can employ to make the study of SRL and AI more generalizable and rigorous.

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