AI-ENABLED SELF-REGULATED LEARNING: A MULTI-LAYER TAXONOMY DEVELOPMENT

Completed Research Paper

Abstract

In light of the widespread adoption of Artificial Intelligence (AI), educators are increasingly exploring innovative applications of this technology within their domain of expertise. Notably, research indicates the capability of AI to facilitate proactive control over the learning process by students, fostering what is commonly referred to as self-regulated learning (SRL). In this vein, our research undertook the development of a taxonomy, thereby contributing to theory and practice by furnishing a comprehensive overview elucidating pertinent dimensions and characteristics intrinsic to AI-based learning systems and their impact on SRL. By incorporating a Technological Mediation Learning perspective and the socio-technical system framework, our taxonomy contributes to a nuanced understanding of AI-based learning systems within the realm of SRL. Consequently, our research establishes a foundational framework for delving into the potentialities of AI-based learning systems, thereby enhancing educational practices and assisting learners in navigating their cognitive processes.

Keywords: Artificial Intelligence, Education, Self-regulated Learning, Taxonomy.

1 Introduction

The use of artificial intelligence (AI) is on the rise, especially in educational settings. The Horizon Report 2023 Teaching and Learning Edition (2023) states that AI represents a key technology expected to significantly influence the future of teaching and learning. The report particularly emphasizes AI-enabled applications concerning predictive, personalized learning. Progress in predictive AI is pervading the development of personalized learning tools, supporting the shift from “one size fits all” technology to personalized learning experiences (EDUCAUSE 2023). Due to its potential to support learning in different contexts, AI has become increasingly important in recent years as a machine-based technique with algorithmic capabilities for prediction, diagnosis, recommendation, and decision-making. The increasing importance of AI in education is also evident from the growing attention in research. In their review, Chen et al. (2022b) examine the number of published articles in the field from 2000 to 2019 and reveal an upward trend, especially since 2012, whereas after this point, 70% of the total articles identified were published. They attribute this upward trend in particular to the increasingly positive findings regarding the effects of AI on learning outcomes and performance.

AI can not only improve learning performance but also support self-regulated learning (SRL) and the development of SRL skills (Molenaar 2022), e.g., by interpreting self-reported protocols of learners (Wang and Lin 2023). SRL refers to the proactive control of the learning process by students to ensure that they reach their learning goals (Zimmerman 2002). SRL is considered one of the most essential skills students need to possess in the 21st century. Especially in online learning environments, engaging in SRL is important for successful learning, as these environments offer learners considerable autonomy regarding their learning process (Jansen et al. 2020). SRL encompasses different phases and includes not only cognitive and metacognitive aspects of learning, but also behavioral, motivational and emotional/affective aspects (Panadero 2017). Previous research indicates that the effective use of SRL strategies and individual variations in self-regulation relate to enhanced learning outcomes (Dever et al. 2023). However, in digital and online learning settings, many learners lack the ability to self-regulate their learning (Azevedo and Feyzi-Behnagh 2011; Jansen et al. 2020).

Despite the growing body of knowledge on SRL and AI in education (Järvelä et al. 2023), there remains a gap in understanding how AI applications can be designed to support SRL and facilitate the development of SRL skills. To date, there is an insufficient understanding regarding the specific building blocks of AI-based learning systems and their distinct impacts on SRL, which hinders the identification of effective SRL support. Our research aims to make a first step towards this research and address this gap by providing a comprehensive overview that presents relevant dimensions and characteristics of AI-based learning systems and their possible impact on SRL. Such an overview that extends beyond technical considerations and incorporates the educational context can be beneficial for describing, classifying, and analyzing learning systems. Therefore, we focus on the following research question:

***RQ**: What are differentiating characteristics of AI-based learning systems in the context of SRL?*

To answer the research question, we design a multi-layer taxonomy of AI-based learning systems incorporating a SRL perspective as kernel theory. In our research we follow the established guidelines of Nickerson et al. (2013) and Kundisch et al. (2022). Taxonomies structure and organize the knowledge of a research topic and thus enable researchers and practitioners to understand and analyze complex subject matter (Nickerson et al. 2013). Within our taxonomy development process, we integrate existing literature through a structured literature review as well as qualitative expert interviews. Throughout our research process, we conducted 12 interviews, including six research experts and additional six industry experts as part of the evaluation of the taxonomy. This ensures a broad perspective on the phenomenon, stemming from ex-ante knowledge, and insights of researchers and practitioners. The final taxonomy comprises 18 dimensions and 65 characteristics, organized in four overarching layers. Our taxonomy serves as a basis for describing AI-based learning systems in the context of SRL, as a scheme for classifying specific learning systems and allows for determining similarities and dissimilarities of corresponding systems. Thereby, we contribute to the understanding of AI-based learning systems in the context of SRL and provide a foundation for further research and practitioners with a first step for the development of such systems.

This work is structured as follows: after our introduction, we provide the theoretical background of our research by presenting the current state of technology-mediated learning environments, AI in education, and SRL as the kernel theory of our study. In section three, we introduce the reader to our methodological approach and report on our research process. This presentation ultimately leads to our final taxonomy which we introduce in section four. Next, section five discusses our findings against the theoretical background and highlighting implication for theory and practice. Finally, we present a summary of our research in section six and highlight possible limitations to it.

2 Theoretical Background

2.1 Technology-mediated learning environments

Recent digital technological developments are enmeshed in the fabric of educational processes (Rabin et al. 2019) enabling technology-mediated learning (TML). This describes "an environment in which the learner's interactions with learning materials (readings, assignments, exercises, etc.), peers, and/or instructors are mediated through advanced information technologies" (Alavi and Leidner 2001, p. 2). The environment represents a combination of the learning context, learning method structures, and learning processes (Gupta and Bostrom 2009). Looking at the learning methods, online learning employs specific combinations of information systems to guide learners (Gupta and Bostrom 2009). This situates the technology at the intersection with social structures making it imperative to focus on the learning process (Alavi and Leidner 2001; Gupta and Bostrom 2009; Hannafin et al. 2004) to predict learning outcomes (Gupta and Bostrom 2009). The underlying information systems varies in complexity as it is either used to facilitate learning as a mere instructional medium or applied as a tool to learn from (Gupta and Bostrom 2009). This might therefore overwhelm learners in the learning environment (Janson et al. 2020) hindering the learning process without sufficient guidance and support (Chen et al. 2020b). Therefore, supporting the individualized learning process through effective interventions is particularly pertinent in the context of TML (Gupta and Bostrom 2009), as learners autonomously navigate their educational journey to form and adapt their learning process (Pintrich 2000; Zimmerman 2002).

2.2 Artificial Intelligence in Education

To support individualized learning processes artificial intelligence in education (AIEd) "[promotes] the development of adaptive learning environments and other AIEd tools that are flexible, inclusive, personalized, engaging, and effective" (Luckin et al. 2016, p. 18). AIEd harnesses the technological replication of human capabilities, encompassing learning, cognition, adaptability, and decision-making functions (Chen et al. 2020a). As such, AIEd is an effective tool to gain a deeper and more nuanced understanding of how educational learning truly unfolds (Luckin et al. 2016) to facilitate teaching, learning, or decision-making. The application field of AIEd spans services both at the institutional and administrative level, as well as those providing academic support for teaching and learning (Zawacki-Richter et al. 2019) to enhance instructional quality (Chen et al. 2020a). This especially holds in distance-learning contexts (Zawacki-Richter et al. 2019) where AI perceives its learning environment and accordingly intervenes through actions (Russell and Norvig 2010). The intervention is increasingly facilitated by technological progress, shifting from computer-based formats to embedded systems (Chen et al. 2020a). Consequently, systems predominantly manifest as digital agents interacting with and responding to the learners needs (Schiaffino et al. 2008).

We differentiate between unilateral or dialogic interaction and communication (Chi et al. 2011) when looking into the areas of AI enhancing the learning experience. The first area focuses on *profiling and prediction*, where AI is utilized to forecast critical aspects of a student's educational journey. This includes predicting admission decisions, registration trends, course selection behaviors, and identifying students at risk of academic failure. It also aids in predicting student withdrawal by analyzing factors like proficiency scores and study habits (Chen et al. 2022b). The second area showcases AI's capability in *automated grading and scoring* with an accuracy comparable to human evaluators (Gierl et al. 2014), along with providing targeted prompts during learning tasks and feedback for skill improvement. The third area encompasses *adaptive systems and personalization*, where AI supports academic advising, career services, and personalizes content based on student behavior (Arslan and Kose 2016). This extends to assist teachers in designing learning experiences and using academic data for guiding and monitoring student progress (Rovira et al. 2017). The fourth area, culminates the aforementioned in an *intelligent tutoring system* to embody a student-centered approach by customizing educational content (Rus et al. 2013) and methodologies to align with individual learning needs (Schiaffino et al. 2008).

2.3 Self-regulated Learning as a Kernel Theory

Self-regulated learning is becoming more important in TML environments and the increased involvement of technology in the learning process. The autonomy of learners requires them to form and adapt their learning process actively and constructively (Pintrich 2000; Zimmerman 2002). As a cyclical process self-regulation is determined by personal, behavioral, and environmental processes (Zimmerman 2002). The process accentuates the role of motivation (Panadero 2017; Zimmerman 2000) to complete the goal-directed activities (Zimmerman 2002). Goal orientation considers how, why and under what environmental conditions people learn (Pintrich 2000). In the learning process, the learner is not just a passive recipient of information but actively and constructively engages in it. This involvement includes the ability to monitor, control, and regulate aspects of cognition, motivation, behavior, and the environment. The learner uses criteria as a basis for progress comparison, adapting as necessary. Personal or contextual factors alone do not solely dictate outcomes such as performance or achievement. Instead, the learner's self-regulation of cognition, motivation, and behavior mediates the relationship between these factors and performance outcomes. Building upon this we understand self-regulated learning as “an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment” (Pintrich 2000, p. 453).

Pintrich's framework (2000) is split in two dimensions: the first dimension delineates the four phases of self-regulation (1) forethought, planning and activation, (2) monitoring, (3) control, and (4) reaction and reflection. The second dimension identifies the four areas for regulation (1) cognition, (2) motivation/affect, (3) behavior, and (4) context. The frameworks are not just theoretical constructs but support thinking and research on SRL (Pintrich 2000) disclosing the needed (meta)abilities of students in TML (Tanner 2012). For instance, AI-based learning systems identify students' SLR strengths and areas for improvement (i.e., phases (1), (4)) and assess their progress (i.e., phase (2Pintrich's framework (2000) is split in two dimensions: the first dimension delineates the four phases of self-regulation (1) forethought, planning and activation, (2) monitoring, (3) control, and (4) reaction and reflection. The second dimension identifies the four areas for regulation (1) cognition, (2) motivation/affect, (3) behavior, and (4) context. The frameworks are not just theoretical constructs but support thinking and research on SRL (Pintrich 2000) disclosing the needed (meta)abilities of students in TML (Tanner 2012). For instance, AI-based learning systems identify students' SLR strengths and areas for improvement (i.e., phases 1, 4) (Pokrivcakova 2019). Further, the system can measure different SRL data types (i.e., phase 2) and assess their progress (i.e., phase 3) (Dever et al. 2022). Finally, the system provides real-time, personalized scaffolding to tailor educational experiences in line with SRL instead of being static (i.e., phase 4) (Lim et al. 2023). Thus, we need to promote the development of adaptive, flexible, and personalized learning environments to guide learning journeys (Zawacki-Richter et al. 2019). Looking forward, the integration of SRL principles with emerging AI technologies presents an exciting frontier for educational research promising even more personalized and effective learning experiences.

3 Method

In our research process, we follow the established recommendations of Kundisch et al.’s (2022) 18-step development process for taxonomies to investigate AI-based learning systems. A taxonomy represents a suitable approach to analyze existing and future systems, to classify and categorize them in the context of self-regulated learning, and thus advance the understanding of the topic.

Before we started the iterative development of our taxonomy, we defined the problem and motivation (*steps 1*), as elaborated in our introduction section. Accordingly, the taxonomy holds relevance for several intended target user groups, including researchers interested in the fields of SRL, artificial intelligence, and digital learning, for example, but also practitioners who are engaged in the design and development of AI-based learning systems (*step 2*). On the one hand, we use the process-driven development perspective to create a tool for classifying objects. On the other hand, we employ a theory-building perspective to derive design recommendations at the end of the work *(step 3*). Based on the purposes and intended users, we define the following meta-characteristic for our taxonomy: *AI-based learning systems in the context of self-regulated learning* (*step 4*). To specify when the taxonomy building process reaches completion, we determine objective and subjective ending conditions, drawing on those proposed by Nickerson et al. (2013) (see Table 1). Furthermore, we defined the following evaluation goals as proposed by Kundisch et al. (2022): *describing*, *classifying*, and *analyzing*. This means that the provided characteristics and dimensions should serve as a basis for describing the phenomenon under consideration, as a scheme for classifying a specific object, and as a basis for determining similarities and dissimilarities of objects (*step 5*). To ensure the accuracy and relevance of our data, we adhered to the contemporary taxonomy approaches outlined by Baier et al. (2023), also incorporating non-exclusive characteristics. This methodology represents an adaption from the framework defined by Nickerson et al. (2013).

Objective ending conditions	**Subjective ending conditions**
• Each characteristic is unique within its dimension (no characteristic duplication). • Each dimension is unique within the taxonomy (no dimension duplication). • No dimensions or characteristics were added in the last iteration. • No dimensions or characteristics were merged or split in the last iteration.	• Concise • Robust • Comprehensive • Extendible • Explanatory

Table 1. Objective and subjective ending conditions

For each iteration of our development process, we first assessed and made a decision on the options for the approach to the iterative development process (*step 6*) and then adopted either an empirical-to-conceptual (inductive steps followed by an e, e.g., *7e*) or a conceptual-to-empirical (deductive steps followed by a c, e.g., *7c*.) approach. At the end of each iteration, we checked for the fulfilment of our pre-defined ending conditions. In total, we conducted four iterations before reaching our ending conditions. We detail our iterations in the following:

Iteration 1: To structure our research area and to address the increasing amount of literature, we choose a conceptual-to-empirical approach as a first iteration for developing the initial taxonomy (*step 6*). For this purpose, we conducted a systematic literature review, following the guidelines of Webster and Watson (2002). Our review comprises the scientific databases Web of Science, AIS eLibrary, IEEE Explore, and EBSCOhost, resulting in a total of 5,739 articles which we thereafter refined following the suggestions of Webster and Watson (2002) to a set of 25 articles, serving as a basis for deriving the first 17 dimensions and 79 corresponding characteristics (*steps 7c-8c*). We organized the dimensions into 5 overarching layers to create a systematic structure and increase the explanatory power of the taxonomy. This process yields the initial version of the taxonomy (*step 10*). Next, we checked the objective ending conditions *(step 11)* with the conclusion that the taxonomy contains very unstructured dimensions and that the characteristics partly overlap and are not completely distinct *(step 12)*. Since the taxonomy did not meet all ending conditions a revision of the taxonomy was necessary.

Iteration 2: For the second iteration we choose an empirical-to-conceptual approach to obtain primary data and to provide empirical evidence (*step 6*). This seems necessary to consider the novelty and specificity of the phenomenon when designing and evaluating the taxonomy. Therefore, we employed semi-structured interviews with research experts based on the guidelines of Myers and Newman (2007). The interviews serve as a source for in-depth knowledge as well as for relevant feedback from experts, which enabled the review, enhancement, and further development of the initial taxonomy. Moreover, the expert interviews helped identifying new characteristics and dimensions. For our interviewee selection, we applied purposeful theoretical sampling (Myers and Newman 2007) until we reached our desired level of saturation. We provide an overview of the expert interviews in Table 2 (*steps 7e-9e*). Within the framework of short author workshops, we recapitulate and discuss the key insights after each interview and determine their suitability regarding our research topic. Subsequently, we incorporated the relevant feedback into the taxonomy, enabling iterative discussions concerning its respective status. This results in a revised version of the taxonomy (*step 10*).

No.	Job title	Discipline	Duration
I01	Researcher	Artificial Intelligence, Educational Technology, Computational Linguistics, Human-computer Interaction, Information Systems	67 min
I02	Researcher	Human-computer Interaction, Information Systems	50 min
I03	Researcher	Educational Psychology, Didactics, Educational Theory	68 min
I04	Researcher	Educational Technology	57 min
I05	Researcher	Information Systems	46 min
I06	Researcher	Educational Technology, Artificial Intelligence	82 min

Table 2. Interviewees for taxonomy iteration two

Subsequent to this second iteration, we checked again whether the taxonomy meets all objective ending conditions *(step 11)*. There is general agreement that the taxonomy does not contain any characteristic or dimension duplications. However, the interviews led to a comprehensive modification of the taxonomy, encompassing the addition, amendment, and removal of several dimensions and characteristics. Consequently, not all objective ending conditions were met, necessitating another iteration (*step 12*).

Iteration 3: In the third iteration, we again choose a conceptual-to-empirical approach (*step 6*). To further refine and revise the taxonomy, we followed the guidelines by Nickerson et al. (2013) and used the knowledge and experience of the authors. Based on our experience in the field, we deduced which dimensions and characteristics are relevant (*steps 7c-8c*). In the third iteration, taking into account the author's knowledge and experience leads to further adjustments to the taxonomy (Kundisch et al. 2022). Again, we checked our taxonomy for all ending conditions (*step 11*). These modifications signify that, even after the third iteration, not all objective ending conditions are met, and thus another iteration is necessary (*step 12*). However, the extent of revision in the third iteration was considerably smaller compared to the previous iteration, indicating a growing level of explanatory power and enhanced stability within the taxonomy.

Iteration 4: Since the resulting taxonomy did not meet all ending conditions, we performed another iteration. For the further enhancement and validation of the taxonomy, we opted for another conceptual-to-empirical approach (*step 6*). Our workshop within the team of authors confirmed the existing dimensions and characteristics and do not lead to any further adjustments of the taxonomy (*steps 7c-8c*). Subsequently, we re-examined the objective ending conditions *(step 11)*. It became evident that each characteristic is unique within its dimension and each dimension is unique within the taxonomy, thus duplications do not exist. Moreover, the fourth iteration did not require any further modifications of the taxonomy. Consequently, after this iteration, the taxonomy met all objective ending conditions (*step 12*). Subsequently, we examined the subjective ending conditions, i.e., whether the taxonomy is applicable. To ascertain the quality of the taxonomy, we further tested it against the following criteria: conciseness, robustness, comprehensibility, extendibility, and explanatory power (Nickerson et al. 2013) and concluding our taxonomy fit for evaluation.

Evaluation: Following the ex-ante evaluation at the end of each taxonomy development iteration we performed an ex-post evaluation. We configured an evaluation considering the purpose of the taxonomy as well as the predefined target groups and evaluation goals, which we measure using appropriate evaluation methods and criteria (*step 15*). Kundisch et al. (2022) propose various taxonomy-related evaluation methods. As AI in education is a relatively new field, only a very small number of learning systems that use AI and explicitly aim to promote SRL are currently available. Thus, we choose semi-structured expert interviews (Myers and Newman 2007) as an evaluation method to assess the taxonomy by experts with proven knowledge and experience in the relevant area. Our evaluation finally involved six experts from related industry sectors to ensure the integration of the practitioners' perspective into the taxonomy *(step 16)*. Table 3 provides an overview of all interviewees.

The practical insights and feedback from these experts contributed to the evaluation and further refinement of the taxonomy. During the interviews, we discussed the individual layers, dimensions, and characteristics with the experts and pursue the evaluation criteria completeness, understandability, and perceived usefulness. These are suitable for evaluating taxonomies and are frequently used, especially in connection with expert interviews (Kundisch et al. 2022).

No.	Job Title	Industry	Duration
I07	Instructional Designer, Strategic Product Manager & Product Owner	Professional Training and Coaching	68 min
I08	Learning & Development Project Manager	Chemical Manufacturing	51 min
I09	Learning and Development Expert & Project Manager	Aviation and Aerospace Component Manufacturing	47 min
I10	Digital Learning Project Manager	Biotechnology Research	60 min
I11	Head of Educational Technologies	Professional Training and Coaching	50 min
I12	Founder & Managing Director	E-Learning Providers	30 min

Table 3. Interviewees for taxonomy evaluation

The expert interviews largely validated our taxonomy. In addition, the findings from the interviews lead to minor revisions of the taxonomy, with all adjustments relating to the layer 'technology' *(step 17)*. The interviews reveal that the learning environment encompasses several dimensions and therefore needs to be considered in a more differentiated way. Hence, we obtained our final taxonomy *(step 18)*.

4 Results

The final version of our taxonomy, after conducting four iterations, comprises 18 dimensions and 65 characteristics. To enhance the understandability of the taxonomy, we specify for each dimension whether the characteristics are mutual exclusive (ME) or non-exclusive (NE). All dimensions and characteristics build on the meta-characteristic and thus refer to AI-based learning systems in the context of self-regulated learning. To add structure to the taxonomy, we organize the dimensions using a socio-technical system perspective, which posits that a system encompasses both a technical and a social subsystem (Gupta and Bostrom 2009). In the technological subsystem, we incorporate the technological design of the system as well as the task the system is intended to accomplish, encompassing a total of eight relevant dimensions. In the social subsystem, we include the educational context and the connection of the user to the system. This results in four layers: technology, scaffolding, educational context, and structure, collectively giving rise to our multi-layer taxonomy of AI-based learning systems in the context of self-regulated learning.

The first dimension of the **technology layer** pertains to ***adaptation***. Adaptation thereby refers to the process of user-specific adaptation of an interactive system's behavior and settings (Schlimbach et al. 2022). This generic term further divides into adaptability and adaptivity. The first characteristic within this dimension focuses on *adaptability*, signifying the user's ability to considerably customize the system by manually adjusting its settings (Schlimbach et al. 2022), e.g., by designing an avatar. The characteristic *static adaptivity* describes systems that can adapt to the user according to the user's ex-ante skills and knowledge (Schlimbach et al. 2022), while *dynamic adaptivity* delineates systems that can continuously adapt to the user. Next, the ***platform*** dimension outlines the platform wherein the system is embedded, specifically referring to the front-end user interface that facilitates user access to the system (Janssen et al. 2020). The system can exist as a standalone *application* or be seamlessly integrated into a *website*. The *social media* characteristic within this dimension describes systems that are integrated into social media platforms like LinkedIn. Additionally, there are systems designed for integration into a *communication and collaboration tool,* such as Microsoft Teams (Janssen et al. 2020). The third dimension addresses the ***hosting*** arrangement of the system. Within this dimension, we identify two central characteristics. On the one hand, the system can be *internally* hosted (Xin and

Levina 2008), providing greater control over the system, e.g. in terms of data privacy. On the other hand, the system can be hosted as a cloud-based *Software-as-a-Service* (SaaS) solution (Mell and Grance 2010), offering scalability and less administrative costs. Fourth, the dimension ***AI function*** describes the range of functionalities that AI can perform. The first characteristic, *recognition*, encompass the task of capturing, processing, and analyzing input data, which can exist in diverse forms, such as images or audio, with the aim of generating information. Another function pertains to *prediction*, the task of estimating and prognosing future events, states, or the development of conditions on the basis of data analyzed. The AI function *recommendation* encompasses direct interaction between the user and the AI system. The characteristic *decision-making* describes AI systems that act autonomously, denoting their capability for autonomous learning and operating (Hofmann et al. 2020; Kieslich et al. 2021). Fifth, the dimension ***communication style*** describes the modality of communication between the user and the system. Firstly, this can take place in a *visual* manner, involving the use of images, videos, diagrams, or animations (Dever et al. 2022). A second mode pertains to *speech-based* communication, which relies on the use of natural language (Mohammadzadeh and Sarkhosh 2018). The third characteristic describes *text-based* communication, where the exchange of information relies predominantly on written text (Song and Kim 2021). Sixth, the ***level of automation*** dimension elucidates the human-machine interaction and collaboration. It provides information regarding the extent to which the AI-based system performs tasks (Vagia et al. 2016). The characteristic *fully automated* describes a system's capability to operate autonomously, with the system being fully in charge and the user being excluded from the loop. In this context, automation means that a machine agent takes over the execution or processing of tasks previously performed by humans (Vagia et al. 2016). In contrast, *partly automated* describes a system, which is assigned particular tasks, but the human operator has certain intervention and control possibilities. We summarize the diverse levels of automation proposed in the literature within this characteristic (Vagia et al. 2016). Seventh, the ***data source*** dimension describes the provenance of user-related data necessary for system adaptation. The first source entails *user input*, which means that the system uses personal data entered directly by the user, including data such as interests or origin. Another data source pertains to *log file data*, in which the system uses information from learning records, including interactions, learning progress, and timestamps. The system can incorporate *external data* or information from external platforms as an additional data source. Finally, the dimension ***system integration*** refers to the potential for integrating a system with other systems or embedding it within a broader platform. The *stand-alone* characteristic describes a system that operates as an independent, closed system. In contrast, the *integrated* characteristic delineates a system capable of seamless integration with other systems through predefined interfaces, which enables the exchange of user data, for example.

The **scaffolding layer** encompasses a total of three dimensions pertaining to the system's role in promoting learning. Scaffolding signifies a form of initial instructional support for learning, tasks completion, and goal achievement (Janson et al. 2020). The first dimension ***scaffolding type*** pertains to the specific nature of support the system provides for guiding and facilitating the learning process. *Procedural* scaffolding serves to support initial orientation and navigation in the system (Cagiltay 2006; Hannafin et al. 2004). *Metacognitive* scaffolding assists the learner in self-reflecting the learning, which means it targets the learner's awareness and monitoring of the learning progress (Hannafin et al. 2004; Jumaat and Tasir 2016). *Conceptual* scaffolding facilitates the meaningful use of the system regarding its underlying didactic purpose (Hannafin et al. 2004; Janson et al. 2020). *Strategic* scaffolding fosters problem-solving by emphasizing alternative approaches and strategies (Janson et al. 2020). Second, the dimension ***feedback level*** encompasses the information the system provides to the user regarding the learning process. *Domain-level feedback* refers to the accuracy of the user's response at the domain level, and it predominantly constitutes correctness feedback (Roll et al. 2011; Zhang and Xu 2022). *Metacognitive feedback* is activated in response to the behavior of the learner during learning, such as the ineffective use of help materials (Roll et al. 2011). *Emotional feedback* acknowledges and addresses the user's emotions. One example is the system's capability to detect when the user is experiencing negative emotions in response to a poor test result. Additionally, we distinguish *progress feedback*, which delivers information concerning the user's learning progress (Long and Aleven 2017). The second dimension ***hint level*** pertains to the type of hint the system provides to support the user. At the *rethink* level, the system provides a hint to support the learner in case of comprehension difficulties in relation to the task, for instance, encouraging the user to try explaining the task to someone else. *Orientation* describes a very general hint to guide the learner towards a suitable next problem step. Hints at the *instrumental help* level provide increasingly detailed, step-by-step explanations for problem-solving. The final hint level involves the *solution* to the problem (Roll et al. 2011).

The **educational context layer** circumscribes the system's embedding within the pedagogical context and contains four relevant dimensions. The dimension ***role of system*** delineates the fundamental role or function the system assumes in supporting the learner. On the one hand, the system can take on a *teacher* role, whereby it imparts learning content and accompanies the entire learning process (Gubareva and Lopes 2020). On the other hand, the system can adopt a *tutor* role by providing short-term assistance only when the user encounters particular difficulties during learning. Another characteristic pertains to the role of a *peer*. The system accompanies the learning process as a kind of fellow student or buddy, assuming the function of transmitting information (Winkler et al. 2021). Furthermore, the system can adopt the role of a *motivator*, encouraging engagement, learning, or participation, often through gamification (Krassmann et al. 2019) or strategies to surmount procrastination (Rodriguez et al. 2019). Lastly, the system can assume an *organizer* role, mainly focusing on offering administrative support to the user, encompassing functions such as course or time management (Gubareva and Lopes 2020). The second dimension ***learning goal*** delineates the specific knowledge dimension that serves as an overarching goal (Anderson and Krathwohl 2001). The characteristic *factual knowledge* pertains to the basic elements of a specific discipline. Factual knowledge is concrete and resides at a low level of abstraction (Anderson and Krathwohl 2001). The characteristic *conceptual knowledge* depicts the knowledge of more sophisticated, organized forms of knowledge (Anderson and Krathwohl 2001). The characteristic *procedural knowledge* pertains to the knowledge of various processes and delves into the 'how' (Anderson and Krathwohl 2001). The fourth characteristic, *metacognitive knowledge*, describes the knowledge about cognition at a broad level along with the awareness and understanding regarding one's own cognition (Anderson and Krathwohl 2001). The third dimension ***learning objective*** comprises specific, measurable competencies the system facilitates in the learning process. The characteristic *remember* pertains to the retrieval of pertinent information from long-term memory, encompassing the cognitive processes of recognizing and recalling. *Understand* involves the construction of meaning from learning context, spanning spoken, written, and graphical communication. The characteristic *apply* means executing a procedure in the case of a known task or implementing knowledge and skills in the case of a new, unfamiliar task. *Analyze* involves the dissection of material into its components, along with the determination of their interrelations and their relation to an overarching structure or purpose. The characteristic *evaluate* pertains to making judgments on the basis of criteria and standards and includes the cognitive processes checking and critiquing. The sixth characteristic, *create*, refers to assembling elements into a consistent or functional whole (Anderson and Krathwohl 2001). The ***educational level*** is the fourth dimension and encompasses five characteristics that delineate the system's target group. The characteristic *primary education* includes users from kindergarten and primary school (Karumbaiah et al. 2022). *Secondary education* comprises both middle and high school students (Bernacki et al. 2015). The characteristic *tertiary education* pertains to users within vocational education, colleges, and universities (Azevedo et al. 2016; Cerezo et al. 2020). *Continuous education* pertains to professional training on the job, essentially referring to education beyond the regular academic system, while *cross-level-education* covers diverse fields and educational levels.

The **structure layer** addresses the system's domain of use as well as the specific phases and areas for SRL in which the system can offer support to the user. In total, this layer comprises three relevant dimensions. The first dimension ***domain*** describes the application domain of the system. We distinguish between *domain specific*, which means that the system targets a specific domain, such as natural sciences, and *cross domain*, which means that the system addresses multiple areas or the domain is not specified more precisely. The second dimension ***areas for SRL*** refer to Pintrich's (2000) SRL framework, delineating the distinct areas for regulation the learner can endeavor to monitor, control, and regulate. Consequently, the characteristics within this dimension depict the areas in which the system can support the learner regarding regulation endeavors: *cognition* pertains to the various cognitive strategies the learner can employ for learning and task execution (Azevedo et al. 2016; Trevors et al. 2014). The regulation of *motivation and affect* refers to the learner's diverse motivational beliefs concerning the self or the task (Chatzara et al. 2016). Regulation of *behavior* concerns the learner's overarching effort to the task, persistence, help seeking, and choice behaviors (Roll et al. 2011). The regulation of *context* includes various facets of the task or learning environment in which the learning occurs (Pintrich 2000). Chen et al. (2022a) introduce an AI service that can assist the user in regulating the context. The system traces the user's eye-gazing points by employing a web camera and an eye-tracking module. The third dimension ***SRL phases*** also pertains to Pintrich's (2000) framework and describes the different phases of self-regulation in which the system can support the learner, thus, we reflect each phase as a separate characteristic. The first phase, *forethought, planning, and activation*, encompasses planning, goal setting, and activating knowledge in relation to the self, the task, and the context (Azevedo et al. 2016; Harley et al. 2018). The *monitoring* phase refers to different monitoring processes that reflect metacognitive awareness of various aspects concerning the self, the task, and the context (Azevedo et al. 2016; Trevors et al. 2014). The third phase pertains to *control* and involves the learner's endeavors in managing and regulating distinct aspects in relation to the self, the task, and the context (Long and Aleven 2017; Roll et al. 2011). The *reaction and reflection* phase comprises various types of reactions and reflections concerning the self, the task, and the context (Pintrich 2000; Zhang and Xu 2022). Figure 1 presents our final taxonomy.

Layers		Dimensions	Characteristics						ME/ NE
Technical subsystem	Technology	Adaptation	Adaptability	Static adaptivity	Dynamic adaptivity				NE
		Platform	Application	Website	Social media	Collaboration and communication tool			NE
		Hosting	Internal	Software-as-a-Service					NE
		AI function	Recognition	Prediction	Recommendation	Decision-making			NE
		Communication style	Visual	Speech-based	Text-based				NE
		Level of automation	Fully automated	Partly automated					ME
		Data source	User input	Log file data	Externa data				NE
		System integration	Stand-alone	Integrated					ME
	Scaffolding	Scaffolding type	Procedural	Metacognitive	Conceptual	Strategic			NE
		Feedback level	Domain-level feedback	Metacognitive feedback	Emotional feedback	Progress feedback			NE
		Hint level	Rethink	Orientation	Instrumental help	Solution			NE
Social subsystem	Educational context	Role of system	Teacher	Tutor	Peer	Motivator	Organizer		NE
		Learning goal	Factual knowledge	Conceptual knowledge	Procedural knowledge	Metacognitive knowledge			NE
		Learning objective	Remember	Understand	Apply	Analyze	Evaluate	Create	NE
		Educational level	Primary education	Secondary education	Tertiary education	Continuous education	Cross level education		NE
	Structure	Domain	Domain specific	Cross domain					ME
		Areas for SRL	Cognition	Motivation/affect	Behavior	Context			NE
		SRL phases	Forethought, planning, motivation	Monitoring	Control	Reaction and reflection			NE

Figure 1. Taxonomy of AI-based learning systems

5 Discussion

Our taxonomy proffers a structured overview of characteristics inherent to these systems that possess the capacity to foster SRL. The outcomes of our investigation furnish an instrument for delineating, scrutinizing, contrasting, and formulating learning systems. By incorporating a TML perspective with a socio-technical system framework (Gupta and Bostrom 2009), we furnish an exhaustive classification of 65 characteristics and 18 dimensions into 4 layers. This approach facilitates the holistic consideration of a socio-technical system—namely, technology, task, people, and structure—thereby advancing the comprehension of AI-based learning systems within the SRL context. To the best of our knowledge, we stand as pioneers in integrating specific SRL phases and domains with diverse design elements and attributes of AI-based learning systems, thereby underscored the imperative of all-encompassing consideration of the nuanced phenomena of SRL. Furthermore, our taxonomy comprehensively encompasses AI-based learning systems, steering clear of exclusive focus on singular system types.

The *technology layer* represents the complex integration of various technological dimensions. During the development we noticed that the varied AI terminology in literature makes clear distinctions challenging. Limited insights into specific AI techniques often leave gaps in understanding AI's capabilities and is best reflected during the interviews where specific functions from a different application focus are mentioned that can help to create or maintain high-quality learning materials, enhancing the didactic value of content (I07, I10, I12). This includes the creation of micro learnings, learning content which is presented to the user in smaller fragments and can be tailored to individual learner needs. Additionally, Karumbaiah et al. (2022) argue, that AI should integrate diverse personal data to enable effective user adaptation. However, our interviews revealed a tension between personalization and technological feasibility. On the one hand, complexity arises through different automation characteristics: I04 illustrated teachers manually providing training data, while I11 described a scenario in which teachers provided an ideal learning path for the user. One the other hand, there is a desire for data-based personalization of the learning experience by using additional personal data (e.g., from log-files or eye-trackers or cultural (Azevedo et al. 2016; Dever et al. 2022; Karumbaiah et al. 2022)) to support SRL. However, the technological configuration is challenged by concerns of data processing and access. Inevitably, the question arises as to how the data (data source) can be exchanged between the systems (hosting) that are embedded differently in the organization (system integration) to trigger the right interventions (AI function). This discourse extends the dialogue surrounding privacy concerns within educational environments, wherein heightened significance is accorded to privacy considerations (Mirbabaie et al. 2022).

The next layer displays the systems incorporation of *scaffolding* functionalities. Research shows that scaffolding does not unilaterally influence all cognitive and metacognitive SRL strategies and the improvement of learning outcomes to the same extent (Duffy and Azevedo 2015; Roll et al. 2011). However, combining different scaffolds can be effective for promoting the development of SRL skills and enhanced learning outcomes (Azevedo et al. 2016; Dever et al. 2022; Song and Kim 2021). Despite these insights, there is a lack of detailed information about the different types of scaffolding and their design characteristics (Devolder et al. 2012). During the taxonomy iterations it became evident that scaffolds are a predominant form of user support. Thereby, we emphasize the use of different scaffolds and scaffolding types to support all SRL phases. This is in line with Janson et al. (2020) who show that scaffolding contributes significantly in complex problem-solving. This underscores the need for a deeper understanding of scaffolding strategies and thus, we incorporate this layer into the taxonomy to showcase the various ways to support SRL in AI-based learning systems. In doing so, our results introduce different design choices for such systems to afford scaffolding support mechanisms. We thus extend the existing scholarly discourse by presenting a methodical framework for designing and evaluating these scaffolding support opportunities.

The *educational context layer* shows contextual factors of the systems environment. The shift from learning from computers to learning with computers (Gupta and Bostrom 2009), inevitably entails the integration of pedagogical considerations (I01). Thus, we incorporate the (revised) taxonomy of Bloom et al. (1956) given its recognition and application in both research and practice, as advised by I01, I03, I11, and I12. This ensures that the technology aligns with the learning goals and objectives in a system, ensuring that the AI's functions are tailored to specific educational needs. Moreover, I11 illustrated the system as an embedded agent, suggesting that AI can act as a “buddy”. This perspective is particularly effective in mitigating the perception of the AI system as merely a data collector, instead framing it as a supportive tool in the learning process, as proposed by Chen et al. (2020a).

The *structure layer* encompasses both the system's domain of application and the particular stages and domains of SRL where the system can provide assistance to the user. We find that AI systems need to cover various areas of regulation and phases, offering distinct support mechanisms. A significant focus of current research is on the regulation of cognition (Harley et al. 2018; Song and Kim 2021; Trevors et al. 2014), extending to practical applications, such as digital assistants (Scheu and Benke 2022). However, there are fewer studies that address the regulation of motivation, an aspect crucial for monitoring and influencing learners' motivation and affect (Chen et al. 2022a). Additionally, systems must not only support cognitive and metacognitive processes but should also specifically focus on facilitating the regulation of motivation and affect (Duffy and Azevedo 2015; Song and Kim 2021) and context (Chen et al. 2022a). While some studies concentrate on supporting the forethought, planning, and activation phases, interviewees suggested that all phases and areas of SRL should be considered in designing AI-based learning systems. This comprehensive approach is vital because self-regulation impacts learners' overall achievement and learning experience. In essence, self-regulated learning involves not just the regulation of cognition but also encompasses motivation, affect, behavior, and context, all of which play a critical role in the four phases of SRL (Pintrich 2000).

Our findings' implications extend to theoretical frameworks and practical applications, offering manifold contributions to the scholarly and applied domains. Through integrating a TML perspective and the socio-technical system framework, our taxonomy advances the comprehension of AI-based learning systems within the sphere of SRL. It achieves this advancement by methodically organizing the intricacies of characteristics and dimensions inherent in these systems. In the enhancement of our understanding regarding SRL and AI in educational contexts, we augment the extant knowledge base (e.g., Winkler et al. 2021; Zawacki-Richter et al. 2019) by synthesizing literature and empirical revelations in our iteratively developed taxonomy. Moreover, our findings establish a foundation for subsequent research endeavors, affording an opportunity to pinpoint future development opportunities in existing AI-based systems. The taxonomy, acting as a systematic framework, equips researchers with a means to methodically organize and categorize information. Notably, it serves as an inaugural point for the recognition of clusters and archetypes inherent in AI-based learning systems, thereby providing a comprehensive overview of existing research.

In the realm of practical implications, our taxonomy offers a structured framework for delineating, analyzing, and contrasting AI-based learning systems in support of SRL. Our assessment underscores a substantial untapped potential within most organizational contexts concerning the integration of AI for learning and SRL support. The taxonomy facilitates communication and decision-making within companies by furnishing a coherent overview of essential dimensions and characteristics, thus establishing a common vocabulary. Furthermore, our results serve as a starting point in the design of AI-based learning systems, elucidating pertinent characteristics and design elements while considering both technical and social components. This, in turn, empowers educational designers and developers to make informed design decisions, accounting for the unique educational context.

6 Conclusion

The persistent discourse surrounding the incorporation of AI in educational environments is anticipated to endure, spurred by technological progressions, notably exemplified by the emergence of generative AI. Through our research we enrich the scholarly conversation in this domain by developing a taxonomy. This taxonomy serves as a methodical framework, facilitating the systematic delineation, analysis, and comparison of AI-based learning systems in their support of SRL processes. As every research endeavor, our work is subject to limitations and offers room for future research. The development process of our taxonomy involved subjective decisions, such as the chosen search string for literature, interviewee assumptions or subjective ending conditions. However, we rigorously followed established guidelines to minimize such biases. Another limitation arises from the fact that the assumption of AI in our literature review is based on the intelligence characteristics of the respective system proclaimed by the authors. We did not independently verify the specific AI components; therefore, we cannot fully validate the degree of AI integration. Future research may investigate AI integration in learning systems in more detail, especially in relation to the specific SRL support. Scholars may also address issues not considered in scope of this study such as collaborative learning effects or ethical aspects of AI application in educational settings. While our research did not explicitly integrate these facets, we maintain a conviction that our work establishes a commendable foundation for delving into the potentialities of AI-based learning systems to enrich educational practices and aid learners in their cognitive processes.

References

Alavi, M., and Leidner, D. E. 2001. "Research Commentary: Technology-Mediated Learning—A Call for Greater Depth and Breadth of Research," *Information Systems Research* (12:1), pp. 1-10 (doi: 10.1287/isre.12.1.1.9720).

Anderson, L. W., and Krathwohl, D. R. 2001. *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*, London: Longman.

Arslan, A., and Kose, U. 2016. "Intelligent e-learning system for improving students'academic achievements in computer programming courses," *The International journal of engineering education* (32:1), pp. 185-198.

Azevedo, R., and Feyzi-Behnagh, R. 2011. "Dysregulated Learning with Advanced Learning Technologies," (doi: 10.20368/1971-8829/517).

Azevedo, R., Martin, S. A., Taub, M., Mudrick, N. V., Millar, G. C., and Grafsgaard, J. F. 2016. "Are Pedagogical Agents' External Regulation Effective in Fostering Learning with Intelligent Tutoring Systems?" in *Intelligent Tutoring Systems*: *13th International Conference, ITS 2016, Zagreb, Croatia, June 7-10, 2016. Proceedings*, A. Micarelli, J. Stamper and K. Panourgia (eds.), Cham: Springer International Publishing, pp. 197-207 (doi: 10.1007/978-3-319-39583-8_19).

Baier, M.-S., Berger, S., Kreuzer, T., Oberländer, A. M., and Röglinger, M. 2023. "What Makes Digital Technology? A Categorization Based on Purpose," *Communications of the Association for Information Systems* (52), pp. 332-384 (doi: 10.17705/1CAIS.05215).

Bernacki, M. L., Nokes-Malach, T. J., and Aleven, V. 2015. "Examining self-efficacy during learning: variability and relations to behavior, performance, and learning," *Metacognition and Learning* (10:1), pp. 99-117 (doi: 10.1007/s11409-014-9127-x).

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., and Krathwohl, D. R. 1956. *Taxonomy of educational objectives: The classification of educational goals. Handbook 1: Cognitive domain*, McKay New York.

Cagiltay, K. 2006. "Scaffolding strategies in electronic performance support systems: types and challenges," *Innovations in Education and Teaching International* (43:1), pp. 93-103 (doi: 10.1080/14703290500467673).

Cerezo, R., Esteban, M., Vallejo, G., Sanchez-Santillan, M., and Nuñez, J. 2020. "Differential Efficacy of an Intelligent Tutoring System for University Students: A Case Study with Learning Disabilities," *Sustainability* (12:21), p. 9184 (doi: 10.3390/su12219184).

Chatzara, K., Karagiannidis, C., and Stamatis, D. 2016. "Cognitive support embedded in self-regulated e-learning systems for students with special learning needs," *Education and Information Technologies* (21:2), pp. 283-299 (doi: 10.1007/s10639-014-9320-1).

Chen, E., Tseng, Y.-H., You, Y.-T., Lo, K.-P., and Lin, C. 2022a. "Preliminary Design of an AI Service to Assist Self-regulated Learning by Edge Computing," in *AIED: International Conference on Artificial Intelligence in Education*, M. M. Rodrigo, N. Matsuda, A. I. Cristea and V. Dimitrova (eds.), Cham: Springer International Publishing, pp. 577-581 (doi: 10.1007/978-3-031-11647-6_119).

Chen, L., Chen, P., and Lin, Z. 2020a. "Artificial Intelligence in Education: A Review," *IEEE Access* (8), pp. 75264-75278 (doi: 10.1109/ACCESS.2020.2988510).

Chen, X., Di Zou, Xie, H., Cheng, G., and Liu, C. 2022b. "Two Decades of Artificial Intelligence in Education: Contributors, Collaborations, Research Topics, Challenges, and Future Directions," *Educational Technology & Society* (25:1), pp. 28-47.

Chen, X., Xie, H., and Hwang, G.-J. 2020b. "A multi-perspective study on Artificial Intelligence in Education: grants, conferences, journals, software tools, institutions, and researchers," *Computers and Education: Artificial Intelligence* (1), p. 100005 (doi: 10.1016/j.caeai.2020.100005).

Chi, M., VanLehn, K., Litman, D., and Jordan, P. 2011. "Empirically evaluating the application of reinforcement learning to the induction of effective and adaptive pedagogical strategies," *User Modeling and User-Adapted Interaction* (21:1), pp. 137-180 (doi: 10.1007/s11257-010-9093-1).

Dever, D. A., Sonnenfeld, N. A., Wiedbusch, M. D., and Azevedo, R. 2022. "Pedagogical Agent Support and Its Relationship to Learners' Self-regulated Learning Strategy Use with an Intelligent Tutoring

System," in *Artificial Intelligence in Education*, M. M. Rodrigo, N. Matsuda, A. I. Cristea and V. Dimitrova (eds.), Cham: Springer International Publishing, pp. 332-343 (doi: 10.1007/978-3-031-11644-5_27).

Dever, D. A., Sonnenfeld, N. A., Wiedbusch, M. D., Schmorrow, S. G., Amon, M. J., and Azevedo, R. 2023. "A complex systems approach to analyzing pedagogical agents' scaffolding of self-regulated learning within an intelligent tutoring system," *Metacognition and Learning*, pp. 1-33 (doi: 10.1007/s11409-023-09346-x).

Devolder, A., van Braak, J., and 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), pp. 557-573 (doi: 10.1111/j.1365-2729.2011.00476.x).

Duffy, M. C., and Azevedo, R. 2015. "Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within an intelligent tutoring system," *Computers in Human Behavior* (52), pp. 338-348 (doi: 10.1016/j.chb.2015.05.041).

EDUCAUSE. 2023. *2023 EDUCAUSE Horizon Report*: *Teaching and Learning Edition*, Boulder CO: EDUCAUSE.

Gierl, M. J., Latifi, S., Lai, H., Boulais, A.-P., and Champlain, A. de. 2014. "Automated essay scoring and the future of educational assessment in medical education," *Medical education* (48:10), pp. 950-962 (doi: 10.1111/medu.12517).

Gubareva, R., and Lopes, R. 2020. "Virtual Assistants for Learning: A Systematic Literature Review," in *Proceedings of the 12th International Conference on Computer Supported Education (CSEDU 2020)*, pp. 97-103 (doi: 10.5220/0009417600970103).

Gupta, S., and Bostrom, R. 2009. "Technology-Mediated Learning: A Comprehensive Theoretical Model," *Journal of the Association for Information Systems* (10:9), pp. 686-714.

Hannafin, M. J., Kim, M. C., and Kim, H. 2004. "Reconciling research, theory, and practice in web-based teaching and learning: The case for grounded design," *Journal of Computing in Higher Education* (15:2), pp. 3-20 (doi: 10.1007/BF02940927).

Harley, J. M., Taub, M., Azevedo, R., and Bouchet, F. 2018. "Let's Set Up Some Subgoals: Understanding Human-Pedagogical Agent Collaborations and Their Implications for Learning and Prompt and Feedback Compliance," *IEEE Transactions on Learning Technologies* (11:1), pp. 54-66 (doi: 10.1109/TLT.2017.2756629).

Hofmann, P., Jöhnk, J., Protschky, D., and Urbach, N. 2020. *Developing Purposeful AI Use Cases : A Structured Method and Its Application in Project Management*, Potsdam, Germany.

Jansen, R. S., van Leeuwen, A., Janssen, J., Conijn, R., and Kester, L. 2020. "Supporting learners' self-regulated learning in Massive Open Online Courses," *Computers & Education* (146), p. 103771 (doi: 10.1016/j.compedu.2019.103771).

Janson, A., Söllner, M., and Leimeister, J. M. 2020. "Ladders for Learning: Is Scaffolding the Key to Teaching Problem-Solving in Technology-Mediated Learning Contexts?" *Academy of Management Learning & Education* (19:4), pp. 439-468 (doi: 10.5465/amle.2018.0078).

Janssen, A., Passlick, J., Rodríguez Cardona, D., and Breitner, M. H. 2020. "Virtual Assistance in Any Context," *Business & Information Systems Engineering* (62:3), pp. 211-225 (doi: 10.1007/s12599-020-00644-1).

Järvelä, S., Nguyen, A., and Molenaar, I. 2023. "Advancing SRL research with artificial intelligence," *Computers in Human Behavior* (147), p. 107847 (doi: 10.1016/j.chb.2023.107847).

Jumaat, N. F., and Tasir, Z. 2016. "A Framework of Metacognitive Scaffolding in Learning Authoring System Through Facebook," *Journal of Educational Computing Research* (54:5), pp. 619-659 (doi: 10.1177/0735633115627824).

Karumbaiah, S., Ocumpaugh, J., and Baker, R. S. 2022. "Context Matters: Differing Implications of Motivation and Help-Seeking in Educational Technology," *International Journal of Artificial Intelligence in Education* (32:3), pp. 685-724 (doi: 10.1007/s40593-021-00272-0).

Kieslich, K., Lünich, M., and Marcinkowski, F. 2021. "The Threats of Artificial Intelligence Scale (TAI)," *International Journal of Social Robotics* (13:7), pp. 1563-1577 (doi: 10.1007/s12369-020-00734-w).

Krassmann, A. L., Nunes, F. B., Bessa, M., Tarouco, L. M. R., and Bercht, M. 2019. “Virtual Companions and 3D Virtual Worlds: Investigating the Sense of Presence in Distance Education,” in *Learning and Collaboration Technologies. Ubiquitous and Virtual Environments for Learning and Collaboration*, P. Zaphiris and A. Ioannou (eds.), Cham. 2019, Cham: Springer International Publishing, pp. 175-192.

Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., and Szopinski, D. 2022. “An Update for Taxonomy Designers,” *Business & Information Systems Engineering* (64:4), pp. 421-439 (doi: 10.1007/s12599-021-00723-x).

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., and Gašević, D. 2023. “Effects of real-time analytics-based personalized scaffolds on students’ self-regulated learning,” *Computers in Human Behavior* (139), p. 107547 (doi: 10.1016/j.chb.2022.107547).

Long, Y., and Aleven, V. 2017. “Enhancing learning outcomes through self-regulated learning support with an Open Learner Model,” *User Modeling and User-Adapted Interaction* (27:1), pp. 55-88 (doi: 10.1007/s11257-016-9186-6).

Luckin, R., Holmes, W., Griffiths, M., and Corcier, L. B. 2016. *Intelligence unleashed*: *An argument for AI in education*, London: Pearson.

Mell, P., and Grance, T. 2010. “The NIST Definition of Cloud Computing,” *COMMUNICATIONS OF THE ACM* (53:6), p. 50.

Mirbabaie, M., Brendel, A. B., and Hofeditz, L. 2022. “Ethics and AI in Information Systems Research,” *Communications of the Association for Information Systems* (50:1), pp. 726-753 (doi: 10.17705/1CAIS.05034).

Mohammadzadeh, A., and Sarkhosh, M. 2018. “The Effects of Self-Regulatory Learning through Computer-Assisted Intelligent Tutoring System on the Improvement of EFL Learner' Speaking Ability,” *International Journal of Instruction* (11:2), pp. 167-184 (doi: 10.12973/iji.2018.11212a).

Molenaar, I. 2022. “The concept of hybrid human-AI regulation: Exemplifying how to support young learners’ self-regulated learning,” *Computers and Education: Artificial Intelligence* (3), p. 100070 (doi: 10.1016/j.caeai.2022.100070).

Myers, M. D., and Newman, M. 2007. “The qualitative interview in IS research: Examining the craft,” *Information and Organization* (17:1), pp. 2-26 (doi: 10.1016/j.infoandorg.2006.11.001).

Nickerson, R. C., Varshney, U., and Muntermann, J. 2013. “A method for taxonomy development and its application in information systems,” *European Journal of Information Systems* (22:3), pp. 336-359 (doi: 10.1057/ejis.2012.26).

Panadero, E. 2017. “A Review of Self-regulated Learning: Six Models and Four Directions for Research,” *Frontiers in Psychology* (8) (doi: 10.3389/fpsyg.2017.00422).

Pintrich, P. R. 2000. “The Role of Goal Orientation in Self-Regulated Learning,” in *Handbook of Selfregulation*, M. Boekaerts, P. R. Pintrich and M. Zeidner (eds.), London: Academic Press, pp. 451-502 (doi: 10.1016/B978-012109890-2/50043-3).

Pokrivcakova, S. 2019. “Preparing teachers for the application of AI-powered technologies in foreign language education,” *Journal of Language and Cultural Education* (7:3), pp. 135-153 (doi: 10.2478/jolace-2019-0025).

Püschel, L., Röglinger, M., and Schlott, H. 2016. “What’s in a Smart Thing? : Development of a Multi-layer Taxonomy,” in *Proceedings of the 37th International Conference on Information Systems*.

Rodriguez, J., Piccoli, G., and Bartosiak, M. 2019. *Nudging the Classroom: Designing a Socio-Technical Artifact to Reduce Academic Procrastination*.

Roll, I., Aleven, V., McLaren, B. M., and Koedinger, K. R. 2011. “Improving students’ help-seeking skills using metacognitive feedback in an intelligent tutoring system,” *Learning and Instruction* (21:2), pp. 267-280 (doi: 10.1016/j.learninstruc.2010.07.004).

Rovira, S., Puertas, E., and Igual, L. 2017. “Data-driven system to predict academic grades and dropout,” *PloS one* (12:2), 1-21 (doi: 10.1371/journal.pone.0171207).

Rus, V., D'Mello, S., Hu, X., and Graesser, A. C. 2013. “Recent Advances in Conversational Intelligent Tutoring Systems,” *AI Magazine* (34:3), pp. 42-54 (doi: 10.1609/aimag.v34i3.2485).

Russell, S., and Norvig, P. 2010. *Artificial Intelligence A Modern Approach*, New Jersey: Pearson Education, Inc.

Scheu, S., and Benke, I. 2022. “Digital Assistants for Self-Regulated Learning: Towards a State-Of-The-Art Overview,” *ECIS 2022 Research-in-Progress Papers*.

Schiaffino, S., Garcia, P., and Amandi, A. 2008. “eTeacher: Providing personalized assistance to e-learning students,” *Computers & Education* (51:4), pp. 1744-1754 (doi: 10.1016/j.compedu.2008.05.008).

Schlimbach, R., Rinn, H., Markgraf, D., and Robra-Bissantz, S. 2022. “A Literature Review on Pedagogical Conversational Agent Adaptation,” *PACIS 2022 Proceedings*.

Song, D., and Kim, D. 2021. “Effects of self-regulation scaffolding on online participation and learning outcomes,” *Journal of Research on Technology in Education* (53:3), pp. 249-263 (doi: 10.1080/15391523.2020.1767525).

Tanner, K. D. 2012. “Promoting student metacognition,” *CBE life sciences education* (11:2), pp. 113-120 (doi: 10.1187/cbe.12-03-0033).

Trevors, G., Duffy, M., and Azevedo, R. 2014. “Note-taking within MetaTutor: interactions between an intelligent tutoring system and prior knowledge on note-taking and learning,” *Educational Technology Research and Development* (62:5), pp. 507-528 (doi: 10.1007/s11423-014-9343-8).

Vagia, M., Transeth, A. A., and Fjerdingen, S. A. 2016. “A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed?” *Applied Ergonomics* (53 Pt A), pp. 190-202 (doi: 10.1016/j.apergo.2015.09.013).

Wang, C.-Y., and Lin, J. J. 2023. “Utilizing artificial intelligence to support analyzing self-regulated learning: A preliminary mixed-methods evaluation from a human-centered perspective,” *Computers in Human Behavior* (144), p. 107721 (doi: 10.1016/j.chb.2023.107721).

Webster, J., and Watson, R. 2002. “Analyzing the Past to Prepare for the Future: Writing a Literature Review,” *MIS Quarterly* (26:2).

Winkler, R., Söllner, M., and Leimeister, J. M. 2021. “Enhancing problem-solving skills with smart personal assistant technology,” *Computers & Education* (165), p. 104148 (doi: 10.1016/j.compedu.2021.104148).

Xin, M., and Levina, N. 2008. “Software-as-a Service Model: Elaborating Client-Side Adoption Factors,” *ICIS 2008 Proceedings*.

Zawacki-Richter, O., Marín, V. I., Bond, M., and Gouverneur, F. 2019. “Systematic review of research on artificial intelligence applications in higher education – where are the educators?” *International Journal of Educational Technology in Higher Education* (16:1), pp. 1-27 (doi: 10.1186/s41239-019-0171-0).

Zhang, Z., and Xu, L. 2022. “Student engagement with automated feedback on academic writing: a study on Uyghur ethnic minority students in China,” *Journal of Multilingual and Multicultural Development*, pp. 1-14 (doi: 10.1080/01434632.2022.2102175).

Zimmerman, B. J. 2000. “Attaining Self-Regulation: A Social Cognitive Perspective,” in *Handbook of Selfregulation*, M. Boekaerts, P. R. Pintrich and M. Zeidner (eds.), London: Academic Press, pp. 13-39 (doi: 10.1016/B978-012109890-2/50031-7).

Zimmerman, B. J. 2002. “Becoming a Self-Regulated Learner: An Overview,” *Theory Into Practice* (41:2), pp. 64-70 (doi: 10.1207/s15430421tip4102_2).