Learning and Individual Differences 122 (2025) 102746

Contents lists available at ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

Personalizing simulation-based learning in higher education☆

Elisabeth Bauer[a,b,*,1], Nicole Heitzmann[c,**,1], Maria Bannert[b], Olga Chernikova[c], Martin R. Fischer[d], Anne C. Frenzel[c], Martin Gartmeier[b], Sarah I. Hofer[c], Doris Holzberger[b], Enkelejda Kasneci[b], Jenna Koenen[b], Christian Kosel[b], Stefan Küchemann[c], Jochen Kuhn[c], Tilman Michaeli[b], Birgit J. Neuhaus[c], Frank Niklas[c], Andreas Obersteiner[b], Jürgen Pfeffer[b], Michael Sailer[a], Ralf Schmidmaier[d], Bernhard Schmidt-Hertha[c], Matthias Stadler[d], Stefan Ufer[c], Andreas Vorholzer[b], Tina Seidel[b,2], Frank Fischer[c,2]

[a] University of Augsburg, Germany
[b] Technical University of Munich, Germany
[c] Ludwig-Maximilians-Universität in Munich, Germany
[d] LMU University Hospital, LMU Munich, Germany

ARTICLE INFO

Keywords:
Simulations
Personalization
Scaffolding
Feedback
Artificial intelligence

ABSTRACT

As digitalization progresses and technologies advance rapidly, digital simulations offer great potential for learning professional practices in contexts such as medical or teacher higher education. The technological advancements increasingly facilitate the personalization of learning support to meet the individual needs of learners, whose diverse prerequisites influence their learning processes, activities, and outcomes. However, systematic approaches to combining technologies with educational theories and evidence are scarce. In this article, we propose to use data on relevant learning prerequisites and learning processes as a basis for personalizing feedback and scaffolding to facilitate learning with simulated practice representations. We connect theoretical concepts with methodological and technical approaches (e.g., using artificial intelligence) for modeling important learner variables as a basis for personalized learning support. The interplay between the learner and the simulation environment is outlined in a conceptual framework which may guide systematic research on personalized learning support in digital simulations.

Educational relevance statement: This paper introduces a conceptual framework, which aims to advance personalized simulation-based learning in higher education. Digital simulations can provide tailored learning experiences that adapt to students' individual differences and needs, using artificial intelligence and other technological advances. This approach might have the potential to transform learning in higher education by increasing student engagement and the effectiveness of learning professional knowledge and skills. The framework is discussed along five central questions of personalized learning, which may guide systematic research on how simulations can accommodate learners' diverse prerequisites and processes. In doing so, the framework provides a starting point for interdisciplinary research collaborations aimed at developing design principles for personalized simulation-based learning in higher

☆ This article is part of a Special issue entitled: 'Future of Learning' published in Learning and Individual Differences.

* Correspondence to: E. Bauer, University of Augsburg, Learning Analytics and Educational Data Mining, Universitätsstr. 10, D-86159 Augsburg, Germany.
** Correspondence to: N. Heitzmann, LMU Munich, Education and Educational Psychology, Leopoldstr. 13, D-80802 Munich, Germany.
E-mail addresses: elisabeth.bauer@uni-a.de (E. Bauer), nicole.heitzmann@psy.lmu.de (N. Heitzmann).

[1] These authors contributed equally to the article and share first authorship.
[2] These authors contributed equally to the article and share senior authorship.

https://doi.org/10.1016/j.lindif.2025.102746
Received 27 March 2024; Received in revised form 17 April 2025; Accepted 17 June 2025
Available online 30 June 2025

1. The future of learning professional knowledge and skills in higher education

Many degree programs in higher education, such as medicine or teaching, aim to prepare students for professional situations of their domain. To support students in acquiring professional knowledge and skills relevant for mastering these situations, innovative instructional approaches are increasingly pursued. Such educational strategies follow the approximation-of-practice approach (Grossman et al., 2009), which suggests experiential learning with authentic practice representations in controlled, low risk learning settings. The idea associated with this approach is to develop professional knowledge and skills while, at the same time, preparing students for applying these in real-life contexts. For this purpose, simulation-based learning is an effective instructional method that can foster complex cognitive skills in higher education (Chernikova, Heitzmann, Stadler, et al., 2020). Through advancements in digitalization and technology, digital simulations offer higher education flexible and scalable opportunities for learning through practice approximations in a controlled yet authentic environment. However, their design needs to balance authenticity and cognitive feasibility to ensure that learners are challenged but not overwhelmed (Chernikova et al., 2024; Fischer et al., 2022; Grossman et al., 2009; Seidel et al., 2015).

The potential of digital simulations is continuously expanding with technological advances, particularly in the area of artificial intelligence (AI), which allows making digital simulations more and more adaptive to learners' individual differences and diverse needs. Harnessing these capacities can become a cornerstone of personalized learning in higher education, provided that conceptual, technological, and ethical considerations can be adequately addressed. In this context, we refer to personalization as "the data-based adjustment of any aspect of instructional practice to relevant characteristics of a specific learner" (Tetzlaff et al., 2021, p. 865).

While there is valuable prior work on personalization both generally and in specific contexts, there has been limited exploration of how personalization can be systematically integrated into simulation-based learning for the development of professional knowledge and skills. This gap is particularly relevant as professional learning requires that learners engage with practice representations that both approximate real-world scenarios and facilitate the structuring and application of knowledge (Boshuizen et al., 2020; Jossberger et al., 2022; Norman et al., 2007), placing high demands on the learning context and personalization approach.

Our paper addresses this gap by presenting a theoretically and empirically informed perspective on integrating personalization into digital simulations for professional learning in higher education. We propose the *SHARP* conceptual framework for advancing research on personalized simulation-based learning in higher education, detailing the interaction between learners and a simulation environment for fostering complex professional practices in higher education (see Fig. 1). We structure the introduction to the framework around five key questions commonly addressed in the literature on personalized learning (e.g., Aleven et al., 2017; Bernacki et al., 2021; Vandewaetere & Clarebout, 2014): (1) Why personalize? (2) What to personalize? (3) Who personalizes? (4) How to personalize? and (5) When to personalize? In doing so, we build on and extend prior frameworks by explicitly linking personalization approaches to the demands of learning in professional contexts through simulations.

The framework emphasizes the importance of modeling different dimensions of individual differences between learners (e.g., cognitive, metacognitive, motivational-affective, and social learning prerequisites and processes) as a basis for personalized learning support specifically in the context of digital simulations for higher education. In the context of learning professional knowledge and skills with simulations, scaffolding and feedback stand out as fundamental approaches for effective learning support (Chernikova, Heitzmann, Fink, et al., 2020). These can be adjusted by recording and integrating relevant learner variables into learner models. Thereby, the framework provides a structured view on the pedagogical reasons for personalizing simulations (e.g., learners with low prior knowledge are more likely experiencing cognitive resource depletion), what is personalized (e.g., complexity of the practice representation), how the personalization may be implemented (e.g., based on learners' tracked performance measures), and when the personalization occurs within the simulation flow (e.g., after each practice representation).

However, there are still many unanswered questions about how to design and implement personalization in digital simulations in a way that effectively addresses learners' individual differences. Many hurdles need to be overcome to realize personalized digital simulations for learning professional skills in higher education at scale—including empirical questions about interactions of various learner characteristics, technical questions about real-time analytics, and ethical questions about data recording and analysis—making personalized simulation-based learning a challenging but visionary, forward-looking approach for higher education. Given the lack of evidence-based design principles for personalized simulation-based learning in higher education, the final

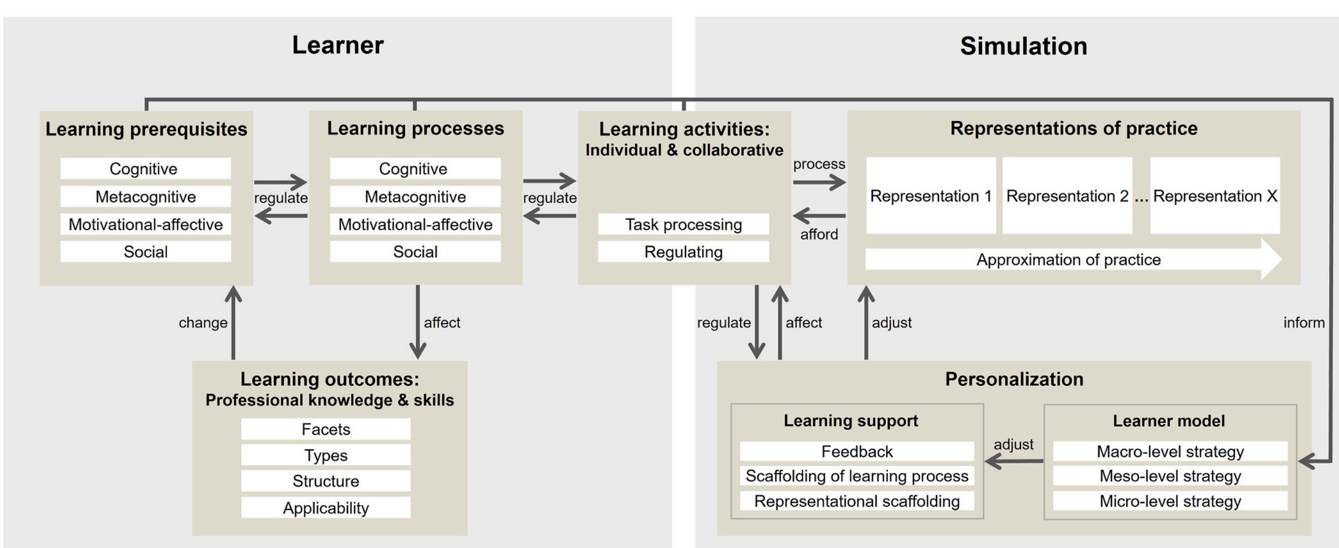

Fig. 1. *SHARP framework for* advancing research on personalized *s*imulation-based learning in higher education.

section of this paper highlights the research needed to make critical advances and pave the road ahead toward personalized digital simulations in higher education.

2. Digital simulations for learning professional practices in higher education

2.1. Professional knowledge and skills

Medicine, teaching, engineering, architecture, nursing, law, design, social work, and other professions are shaped by their members' shared knowledge and skills (Blömeke et al., 2015; Goodwin, 1994; Grossman et al., 2009). The collective patterns of professionals' activities in specific practice situations and the underlying knowledge and skills define what is subsumed as *professional practices* (Bauer et al., 2020; Behling et al., 2022; Fischer et al., 2022; Gherardi, 2009; Goodwin, 1994; Kelly, 2008; Seidel et al., 2021). Preparing future professionals for acting adequately in professional practice situations is a goal that is increasingly adopted by higher education programs, for example, in teacher education (Floden et al., 2020) and medical education (Frank et al., 2010).

To develop practice-oriented curricula, in several professions, there are efforts to understand professional practices that evolved therein, for example, by identifying professional core practices, such as core practices of teaching (CPoT; Grossman, 2021) and entrustable professional activities in medicine (EPAs; Amiel et al., 2021; for an overview of CPoT and EPAs see Fischer et al., 2022). When comparing various domain-specific frameworks, it is evident that certain types of practices, like diagnosing or intervening, are relevant for professionals across different domains. Diagnosing classifies phenomena (e.g., student difficulties or patient symptoms) based on evidence that is often not directly observable but must be generated and evaluated in the form of observable cues (e.g., a student's facial expression or a patient describing discomfort; Heitzmann et al., 2019). Diagnostic conclusions often lead to interventions aiming for positive change (e.g., in problematic conditions of clients) through activities such as designing, selecting, implementing, evaluating, and redesigning intervention measures, as well as engaging in argumentative communication about the intervention with others (Richters et al., 2024). Frameworks, such as CPoT and EPAs, help conceptualize practice-oriented learning objectives for professional learning in higher education. Such professional learning should focus on facilitating theoretical understanding, practical skill training, and experiential learning (Shulman, 1998), enabling future professionals to develop the knowledge for acting in professional practice situations (Seidel et al., 2024; Seidel, 2022).

A professional knowledge base can be characterized by its knowledge facets, types, structure, and applicability. *Facets of knowledge* categorize knowledge into content areas. For example, in teaching, professional knowledge is commonly distinguished as content knowledge (i.e., subject-specific knowledge), pedagogical knowledge (i.e., general knowledge about teaching and learning), and pedagogical content knowledge (i.e., knowledge about subject-specific teaching strategies; Shulman, 1987). *Types of knowledge* describe different knowledge representations, such as conceptual knowledge (i.e., models, principles, categories, and schemas) and strategic knowledge (i.e., methods and approaches for solving specific tasks; Förtsch et al., 2018). *Structure of knowledge* addresses the development of macro-concepts through a process called encapsulation, where theoretical knowledge applied to practical cases leads to compilation and abstraction processes; based on these macro-concepts, problem-specific scripts develop that help actors remember, decide, and act quickly, thus achieving better solutions (Boshuizen et al., 2020; Norman et al., 2007). *Applicability of knowledge* to professional situations and problems reflects how well (future) professionals can apply professional knowledge in specific practice situations (Bromme & Tillema, 1995). This can be captured by situation-specific performance indicators: process indicators (e.g., diagnostic activities; Heitzmann et al., 2019) and outcome measures (e.g., judgment accuracy; Norman, 2005; Urhahne & Wijnia, 2021; or quality of arguments for justifying the judgment; Bauer et al., 2022). These dimensions help outline professional knowledge essential for acting in professional practice situations.

2.2. Approximating practice with digital simulations to learn professional knowledge and skills

To acquire knowledge essential for professional practice and enhance its structure and applicability, learners need to gain experience within relevant practice situations or cases (Boshuizen et al., 2020; Jossberger et al., 2022; Norman et al., 2007), driving higher education to implement experiential learning and reflection. Using representations of practice (i.e., of practice situations or cases) in higher education, professional practice can be approximated in a risk-free manner (Grossman et al., 2009). Representations used for approximating practice should incorporate key characteristics of the professional practice situations being represented (Fischer et al., 2022). In addition, the approximation-of-practice approach suggests decomposing professional practice situations to select and adjust practice representations that cover important aspects of practice without overwhelming learners with the full demands of professional practice (Fischer et al., 2022; Grossman et al., 2009; Seidel et al., 2015).

Simulations—models of natural, social, or artificial systems in which certain features can be manipulated—provide an effective means for approximating practice with relevant practice representations in higher education programs (Fischer et al., 2022; Heitzmann et al., 2019; Lehtinen, 2023). The simulation-based learning approach incorporates elements of situated learning, problem-based learning, and case-based learning (Hmelo-Silver, 2004; Kolodner, 1992; Lave & Wenger, 1991; Wood, 2003). By engaging in professional activities via interactive representations of practice, learners familiarize themselves with the demands of professional situations. Results of meta-analytic studies suggest that simulation-based learning yields large effects for higher education (Chernikova, Heitzmann, Stadler, et al., 2020). Simulations span from analogue role-playing exercises and document-based learning formats to digital multimedia learning environments, and advanced digital applications employing Virtual and Augmented Reality. Simulations with high authenticity are associated with larger effects compared to less authentic simulations. However, functional correspondence to real-world tasks (i.e., functional authenticity) seems more crucial for cognitive learning outcomes than physical resemblance (i.e., physical authenticity; Chernikova, Heitzmann, Stadler, et al., 2020; Hamstra et al., 2014; Norman et al., 2012).

Simulations of professional practices are often conceptualized as skill training. Simulation-based learning environments in medical and teacher education can effectively advance complex knowledge and skills essential for professional practice. In medical education, simulations are widely used to foster diagnostic reasoning, including gathering patient data, formulating differential diagnoses, and justifying decisions under uncertainty (Braun et al., 2019; Cook et al., 2012). Virtual patient simulations provide opportunities to engage in realistic diagnostic decision-making while receiving feedback that promotes reflection. In teacher education, simulations can, for example, be used to train complex skills such as diagnosing the mathematical skill level of students (Nickl, Sommerhoff, Böheim, et al., 2024). These environments offer a controlled space to practice the knowledge and skills critical for professional practice.

To systematically approximate professional practice, a simulation targeting a professional practice may involve multiple simulated practice representations to offer learners repeated training and confront them with a variety of practice scenarios. The sequencing of the individual representations may follow an approximation strategy that incorporates the sequencing principle of increasing difficulty: guiding learners to increasingly realistic representations of practice, through which they progress to representations with high demands and responsibilities that are similar to real professional practice (Collins et al., 1989; Fischer et al., 2022; Koedinger & Aleven, 2007; Seidel et al., 2017; van Merriënboer, & van, & Kirschner, P. A., 2017). Experienced challenges such as unsuccessful solution attempts or errors provide valuable learning opportunities through internal feedback, when learners compare their current knowledge and skills against reference information (Black & Wiliam, 2009; Jossberger et al., 2022; Narciss, 2013; Nicol, 2021; Zimmerman, 1989). Learners' errors have less severe consequences in simulations compared to real practice contexts; therefore, they are less associated with high emotional arousal, that might be detrimental for learning (Tulis et al., 2018). Moreover, simulations facilitate adjustment strategies such as pausing to reflect an error or discuss with collaborating learners. Through these and other mechanisms, learning processes in simulations address cognitive, metacognitive, motivational-affective, and social dimensions of learning (D'Mello & Graesser, 2012; Järvelä et al., 2019; Mayer, 2014; Pekrun & Linnenbrink-Garcia, 2014; Zimmerman & Schunk, 2011).

Especially digital simulations offer high potential by taking advantage of the growing digital infrastructure in higher education and making simulation-based learning accessible to large numbers of students. Digital simulations are technology-driven applications representing real-world systems, processes, or practices (Gegenfurtner et al., 2014; Heitzmann et al., 2019). Digital simulations allow learners to engage with dynamic representations of tasks, roles, systems, or practices. In higher education, they are used to foster professional skills by enabling learners to actively explore, make decisions, and receive feedback within authentic scenarios (Chernikova, Heitzmann, Stadler, et al., 2020). Digital simulations are highly scalable, provided that sufficient infrastructure is available. Moreover, advancements in technology are progressively facilitating the design and implementation of digital simulations. Especially with the increasing popularity and accessibility of generative AI models, such as GPT (OpenAI, 2023), LLaMA (Touvron et al., 2023) and many more, the possibilities for automatically generating content and learning materials (e.g., case studies and dialogues), and for developing digital learning environments are significantly enhanced. As a range of studies and theoretical frameworks have highlighted, the media design has substantial effects on learning processes in digital learning environments, such as digital simulations (Martin et al., 2022; Mayer, 2014; Mutlu-Bayraktar et al., 2019; Schneider et al., 2018). In addition, technological advances facilitate the personalization of digital simulations. For example, integrating multimodal foundation models, such as Gemini (Gemini Team Google et al., 2023), can be useful for tailoring learning support or content to individual learners (Dai & Ke, 2022; Kasneci et al., 2023; Küchemann et al., 2024). Therefore, these technological advancements offer high potential for enriching the media design of digital simulations, creating representations of practice with varying degrees of difficulty, and personalizing learning support to match learners' individual differences and diverse needs.

3. Personalized learning support in digital simulations for higher education

To conceptualize personalized learning support in digital simulations for higher education, our framework integrates relevant theoretical foundations with methodological and technical considerations. Approaches to personalized learning have often been characterized by a focus on methodological and technical dimensions—such as the timing, frequency, method, and control of personalization— meaning that more emphasis is needed on the theoretical underpinnings and empirical findings that inform effective personalization (Bernacki et al., 2021; Rong et al., 2023; Walkington & Bernacki, 2020).

Therefore, our framework builds on previous research that has addressed the issue of integrating theory and technology. For example, Aleven et al. (2017) proposed the Adaptivity Grid, a framework that systematically organizes personalization across dimensions such as goals, targets, and methods of adaptation, and levels of granularity. Within this framework, they introduced a three-loop model—design loop, task loop, and step loop—that reflects increasingly fine-grained instructional personalization, from long-term system redesign to real-time, individualized feedback. This model illustrates how adaptive systems can support learning by responding dynamically to student needs at multiple levels of interaction. Complementary work by Plass and Pawar (2020) emphasizes the importance of selecting personalization variables that are both instructionally relevant and sufficiently varied across learners. Their contributions also offer a granular typology of personalization strategies along with illustrative exemplars, highlighting how personalization can be designed and studied across multiple educational contexts. Bernacki et al. (2021) synthesize the growing body of research on personalized learning into a comprehensive framework that maps personalization along dimensions such as learner characteristics, contexts, and instructional purposes. This framework provides conceptual orientation for describing, comparing, and extending personalization designs in research, implicitly underscoring the need to bridge broad theoretical models with context-specific applications such as those required for simulation-based learning in higher education. Complementary strands of research focus on domain-specific implementations of personalized learning—for example, in K–12 education (Hardy et al., 2019), higher education (Fariani et al., 2023), or in relation to specific approaches to learning such as self-regulated learning (Steinert et al., 2024). Despite these valuable models, limited work to date has explored how personalization can be systematically integrated into simulation-based learning to support the development of professional knowledge and skills. This gap is especially relevant given the demanding nature of professional learning, which requires learners to engage with representations of practice that approximate real-world contexts and support the structuring and application of knowledge (Boshuizen et al., 2020; Jossberger et al., 2022; Norman et al., 2007).

Existing personalized learning frameworks (e.g., Aleven et al., 2017; Plass & Pawar, 2020; Bernacki et al., 2021) provide overarching models for tailoring instruction to individual learner needs, delineating key dimensions of adaptivity (e.g., cognitive, motivational, and affective). Simulations extend these personalization possibilities beyond conventional learning environments by allowing learners to engage in iterative trial-and-error practice on complex tasks without real-world risk, thereby providing a safe, feedback-rich environment for skill development. Such simulation environments also provide structured opportunities for reflection (e.g., pausing to consider outcomes or incorporating dedicated reflection phases). In addition, simulations generate fine-grained data on learners' actions, enabling in situ personalized scaffolding and feedback. Adaptive supports can be dynamically triggered by deviations in a learner's problem-solving trajectory; for example, the system might offer hints or prompts to guide the learners actions, or adjust the scenario's representation to aid understanding (i.e., process-oriented and representational scaffolding). These real-time, context-specific support capabilities surpass what is addressed by existing personalization frameworks that—due to their broader scope or different focus—do not offer a theoretical account of the unique affordances of personalizing simulation-based learning (e.g., balancing task complexity with help of embedded supports). Therefore, a framework that elaborates on personalization in simulation-based learning of professional knowledge and skills can offer opportunities for advancing this area of research and education.

Introducing the SHARP framework (see Fig. 1), we address five key questions commonly addressed in the literature on personalized learning (e.g., Aleven et al., 2017; Bernacki et al., 2021; Vandewaetere & Clarebout, 2014): (1) Why personalize? (2) What to personalize? (3) Who personalizes? (4) How to personalize? and (5) When to personalize? In addressing these questions, we consider how learners' individual differences—such as variations in prior knowledge, metacognitive capacities, and motivational beliefs—can serve as meaningful input for personalization, particularly in simulation-based learning. However, there are still many challenges and unanswered questions about the design and implementation of personalized digital simulations. Therefore, our framework provides an overview of current options and challenges concerning the personalization of digital simulations, including approaches to modeling learners and tailoring support through AI-driven systems (for a summary, see Table 1; for two examples of personalized simulations, analyzed along the key questions, see Table 2). In doing so, we aim to guide systematic research toward the development of design principles for personalized simulation-based learning in higher education.

3.1. Why to personalize?

Learners with varying characteristics differ regarding what representations of practice are challenging for them and where in the learning process they encounter which difficulties. Individual differences in learners' prerequisites, processes, and activities may result in diverse needs for learning support. Therefore, when learning with digital simulations, students may greatly benefit from personalization. Through personalized support, educational programs can specifically target

Table 1
Overview of typical questions as well as options and challenges when approaching personalization of digital simulations.

Questions	Options	Challenges
1. Why to adapt?	Learners' individual differences and diverse needs related to their: • Cognitive, metacognitive, motivational-affective, and social learning prerequisites • Cognitive, metacognitive, motivational-affective, and social learning processes • Learning activities related to task processing and regulating	• Considering interaction effects of learner variables (i.e., combinations of variables forming learner profiles) • Considering collaborative learners' joint composition of learning prerequisites • Identifying which variables provide sufficient heterogeneity for personalization
2. What to adapt?	Learning support measures: • Learning process scaffolding • Representational scaffolding • Feedback	• Choosing the right learning support for learners with different characteristics • Balancing learner support with the potential obtrusiveness of support measures
3. Who adapts?	Adjustments can be made: • For the learner, by an instructor or a computer (i.e., adaptivity) • By the learner (i.e., adaptability)	• Choosing the right personalization approach for learners with different characteristics • Balancing learner support with learner autonomy
4. How to adapt?	Creating learner models through: • Video, audio, text, logfile, eye tracking or other physiological measures, tests and questionnaires, all of which can be used to infer learning prerequisites and learning processes (i.e., recording learner data) • Supervised, unsupervised, semi-supervised, self-supervised, and reinforcement learning methods (i.e., analyzing learner data)	• Limiting the obtrusiveness of data recording • Ensuring reliability, validity, and interpretability of measurements • Integrating multimodal data • Balancing prediction accuracy with model interpretability • Ensuring data protection and privacy • Interpreting learner behaviors in ill-structured, authentic simulation tasks.
5. When to adapt?	Adjustments can be made: • Before the start of the simulation (i.e., macro-level) • After completion of a significant segment, e.g., one simulated practice representation (i.e., meso-level) • Within smaller learning segments, e.g., during practice representations using real-time analyses (i.e., micro-level)	• Choosing the right personalization strategy for more or less stable or volatile learner variables • Determining the stability or volatility of learner variables

Table 2
Examples of personalized support in digital simulations, described along the guiding questions.

Questions	Example: Adaptive scaffolding in a video-based simulation for learning pedagogical content knowledge (PCK) in biology teacher education (Irmer et al., 2024)	Example: Adaptive feedback in a document-based simulation for learning diagnostic reasoning in teacher education (Bauer et al., 2025)
1. Why to adapt?	• Learners' levels of prior PCK vary, which impacts their effective planning and reflection across multiple simulated practice representations of teaching situations. • Learners with low prior PCK struggle with enacting knowledge due to the lack thereof and thus might benefit from scaffolding that provides input on relevant knowledge aspects (cPCK-scaffolds). • Learners with high prior PCK might benefit from scaffolding that supports them in applying their available knowledge (pPCK-scaffolds).	• Learners vary in their levels of prior knowledge and self-regulation skills, resulting in challenges during the processing of detailed practice representations about students' learning difficulties. • Especially low performing learners might experience difficulties with integrating feedback about detailed case information in the own knowledge structures without cognitive resource depletion. • Learners' performance in reasoning about the case might indicate their difficulties regarding cognitive processing (e.g., which case information they considered) and learning activities related to task processing (e.g., how information was generated).
2. What to adapt?	• Learning process scaffolding in this simulation aims to adjust to learners' prior PCK, providing cPCK-scaffolds to learners with low prior PCK and pPCK-scaffolds to learners with high prior PCK.	• Adaptive feedback in this simulation aims to adjust to the learners' diagnostic reasoning performance, highlighting achievements and difficulties in learners' cognitive processing and learning activities.
3. Who adapts?	• Adjustments are initiated and supervised by the higher education teacher (i.e., adaptivity).	• Adjustments are made by the computer (i.e., adaptivity) to spare learners' cognitive and self-regulatory resources.
4. How to adapt?	• A pre-test assesses learners' prior PCK to determine the type and level of scaffolding each learner receives. Adaptations are assigned according to a predefined cut-off in learners' prior PCK based on the initial PCK assessment.	• Learners' text data (written diagnostic reasoning) is used to infer the achievements and difficulties in learners' cognitive processing and learning activities. • An artificial neural network (i.e., a supervised learning method) was trained to automatically recognize relevant case information and learning activities in learners' text data and automatically select predefined feedback paragraphs.
5. When to adapt?	• The adaptation is determined before the learners engage with the simulation, based on their prior PCK scores. This adaptation sets the stage for the entire learning session, providing a consistent level of support tailored to the initial assessment (i.e., macro-level personalization).	• After learners submitted their responses, a real-time analysis enabled making adjustments to the feedback message within one practice representation (i.e., micro-level personalization) to dynamically respond to learner performance changes across practice representations.

learners' difficulties, aiming to optimize learners' engagement with simulated situations to maximize the educational benefits of simulation-based learning (Chernikova et al., 2025).

3.1.1. Learning prerequisites

The effectiveness of simulation-based learning is affected by the individual differences in learners' prerequisites, which influence how learners process and engage with simulations (e.g., Bichler et al., 2020; Huber et al., 2015; Kalyuga, 2007; Pieger & Bannert, 2018; Seufert, 2018). When learners notice cues in a simulated situation, their learning prerequisites—cognitive, metacognitive, motivational-affective, and social—are activated and regulate their learning processes and activities (e.g., cue processing), which in turn may affect the learning outcomes and thereby change learners' prerequisites.

Cognitive learning prerequisites include general cognitive abilities (e.g., Bichler et al., 2020), such as analytic and complex problem-solving abilities, important for novel learning situations where relevant knowledge has not yet been acquired. However, the more task-specific prior knowledge is available, the greater its importance for task processing (Hetmanek et al., 2018). In higher education, it is notable that while there might be less discrepancy among students regarding their general cognitive abilities, there remains a wide spectrum in terms of their prior knowledge. This implies that accommodating individual differences in task-specific prior knowledge can be crucial for effective simulation-based learning in higher education.

Metacognitive learning prerequisites encompass knowledge about one's cognitive processes and the metacognitive skills needed for self-regulation activities, such as goal setting, planning, self-control, monitoring, and reflection (e.g., Azevedo, 2009; Zimmerman, 1989). These have been shown to play a critical role in regulating learning processes and, consequently, in achieving learning outcomes (Bannert et al., 2014; Engelmann & Bannert, 2021; Lim et al., 2021; van der Graaf et al., 2022). Simulations afford learners considerable flexibility to experiment with problem-solving strategies and reflect on their actions without severe consequences, suggesting potential benefits of support that is personalized to individual differences in learners' metacognitive prerequisites to facilitate their coping with the demands of simulation-based learning.

Motivational-affective learning prerequisite are crucial for initiating and persisting in actions in learning (Hidi & Renninger, 2006). Individual differences in prerequisites such as interest in the learning content and environment significantly influence engagement with simulations, especially in higher education scenarios where students might work independently before sharing insights in their seminars (Bernacki & Walkington, 2018; Kron et al., 2022). Additionally, motivational factors like students' perceived success expectancy and subjective task value regulate learners' engagement in simulation-based learning, yet the impact of these expectancy-value components on learning outcomes varies considerably by context and construct operationalization, highlighting the situational nature of motivational processes (Holzberger et al., in-principle accepted, 2024; Nickl, Sommerhoff, Böheim, et al., 2024). Nonetheless, adjusting the level of task difficulty and providing additional support to sustain engagement might be vital for learners with lower motivational-affective prerequisites.

Social learning prerequisites include social knowledge and skills for a broad scope of social interactions (Schneider et al., 2017) as well as specialized forms for professional interaction with clients (e.g., physician's patient communication or teachers' communication with students and parents; Gartmeier et al., 2015) and collaboration with colleagues of the same or a different specialization (Radkowitsch et al., 2021). Such social knowledge is stored in internal knowledge structures or cognitive scripts (e.g., internal collaboration scripts; Kollar et al., 2006). If learners have not yet developed such cognitive scripts, this can negatively impact the learning benefits of simulated social interaction and collaboration, suggesting that the learners might require higher degrees of external guidance to support their learning.

Interplay and relevance of learning prerequisites can vary, as practice situations differ in their demands (e.g., including or excluding social interaction; Fischer et al., 2022) and different learning prerequisites may facilitate or hinder each other (e.g., interest and motivation can influence prior knowledge activation). This complexity underscores the need for further research on learner profiles, exploring how different combinations of characteristics affect learning processes and outcomes and interact with varying demands of different practice situations (e.g., Kron et al., 2022; Nickl, Sommerhoff, Böheim, et al., 2024). For example, in a simulation designed to train preservice teachers in diagnostic skills, Nickl, Sommerhoff, Böheim, et al. (2024) noted that learners with above-average cognitive prerequisites (i.e., prior knowledge) tended to demonstrate higher diagnostic accuracy and invested more time, compared to those with below-average cognitive and motivational prerequisites but also those with above-average motivation but lower cognitive prerequisites. This suggests that high motivation is important but cannot compensate for insufficient prior knowledge. Since most current research predominantly examines individual learning prerequisites in isolation, further studies are essential to comprehensively understand how these elements interact within learner profiles during simulation-based learning. Additionally, in collaborative simulation-based learning, the composition of group members' learning prerequisites becomes crucial (e.g., Weinberger et al., 2007), suggesting research on a layered dimension that might extend personalization beyond individual learning needs to including group dynamics.

3.1.2. Learning processes

During simulation-based learning, students' learning prerequisites are activated and regulate the learning processes (e.g., Seufert, 2018). These processes then regulate the learning activities and affect the learning outcomes. For example, when interacting with simulated practice situations, learners perceive and process cues, including visual and verbal information, and engage in learning activities, through which the simulation might reveal more cues, enriching the task-relevant information. Latent learning processes become inferable through the learning activities (see subsequent section) and through further behavioral manifestations such as verbalizations or eye movement (see section *4. How to adapt?*). Like learning prerequisites, learning processes span cognitive, metacognitive, motivational-affective, and social dimensions.

Cognitive learning processes in simulations—from the view of multi-memory models—include learners' processing of sensory information in their working memory, using prior knowledge from long-term memory for encoding (Gegenfurtner et al., 2023; Sweller et al., 2019). The capacity of working memory is constrained, influenced by the structure of prior knowledge and the working memory resource depletion resulting from cognitive effort (Chen, Castro-Alonso, et al., 2018). Information, once processed, is integrated through elaborating and organizing activities into long-term memory, forming the basis for future learning and application (Stern, 2017). This integration process is further explained by the knowledge restructuring through case processing theory (KR–CP; Boshuizen et al., 2020), which posits that learning through cases (i.e., representations of practice) leads to the dynamic adjustment of cognitive schemata that enhance expertise development, especially in fields where there is a strong link between academic knowledge and professional practice. Individual differences such as expertise dependent differences in how learners process, integrate, and restructure knowledge underscore the importance of personalized cognitive support in simulation-based learning for professional knowledge and skills, particularly as these simulations can be demanding for learners' cognitive resources.

Metacognitive learning processes involve learners' awareness and control over their learning (Azevedo, 2009; Bannert et al., 2014; Zimmerman, 1989), critical for effectively navigating a simulated situation and adjusting solution approaches based on ongoing feedback and reflection. Metacognitive processes are intertwined with cognitive processes and influenced by metacognitive and cognitive learning prerequisites, determining, for example, how learners analyze and plan the learning tasks (Lim et al., 2021). Metacognition plays a crucial role in deep reflection of failures within simulations (Zhang & Fiorella, 2023). Adapting learning support to individual differences in learners' metacognitive processes, such as non-ideal strategy adjustments after failure, might prevent learners' shallow processing and facilitate their deep reflection and learning from errors (Heitzmann et al., 2023).

Motivational-affective learning processes include motivational states and processes that, according to self-determination theory, can range from external to self-determined forms (Deci & Ryan, 2004). Self-determination, characterized through feeling competent, autonomous, and socially related, fosters intrinsic motivation and positive affective states, such as students' enjoyment during learning (Krapp, 2005; Pekrun, 2006). Such motivation and positive emotions enhance volitional processes, resulting in deeper and longer engagement in learning activities and, consequently, higher learning outcomes (Pekrun & Linnenbrink-Garcia, 2012; Schiefele et al., 2003). Simulations that cater to learners' situation-specific motivational-affective needs (catch component of interest) might help sustain engagement and facilitate the development of a trait interest in the subject matter (hold component; Knogler et al., 2015), contributing to students' ongoing professional development. Considering individual differences in motivational-affective learning processes for targeted support while learning with simulations might be instrumental in fostering sustained interest and engagement.

Social learning processes underscore the importance of learning from and with others—both in terms of simulated social interaction and collaborative simulation-based learning. Theories such as vicarious or observational learning highlight how observing models and mentally rehearsing observed activities can enhance learning (Bandura, 2008; Jarodzka et al., 2013; Rummel et al., 2009). In simulations, social learning extends to the co-construction of knowledge, where learners refine and possibly assimilate their own individual understandings through activities such as sharing insights and negotiating meaning, which may result in modifying the ideas of other learners (Dubovi & Tabak, 2020). The effectiveness of these social learning processes can be influenced by the composition of the learner group, suggesting that strategic grouping based on similarity or complementarity of knowledge and skills but also strategic support of social learning processes might further enhance learning outcomes in simulations that involve social learning processes (Radkowitsch et al., 2021; Weinberger et al., 2007).

3.1.3. Learning activities

Learning prerequisites and processes often are latent learner variables, which regulate and thereby become evident in *learning activities*, that is, learners' interactions with a simulation environment, learning materials, or peer learners. Such learning activities may be aimed at processing the learning task and regulating the learning experience. When learning is conducted collaboratively, these activities take on an added collaborative layer, incorporating group dynamics alongside individual actions.

Task processing in simulations encompasses a wide range of cognitive activities, including, but not limited to noticing, inquiry, problem-solving, reasoning, interpreting, explaining, argumentation, design, decision-making, and intervention. The analysis of these task-processing activities in various situations and professional fields are facilitated by conceptual frameworks, such as the epistemic activities framework (Fischer et al., 2014) or the professional vision framework (Seidel & Stürmer, 2014). The epistemic activities framework, for example, categorizes a variety of actions such as generating hypotheses, constructing and redesigning artifacts, generating and evaluating evidence. This framework has proven useful across multiple professional fields, including medicine, economics, teaching, and social work (Bauer et al., 2020; Berndt et al., 2021; Ghanem et al., 2018), as it allows for a detailed understanding of how learners approach epistemic tasks in simulations and other contexts and helps to identify unproductive or erroneous behaviors that often indicate insufficient task-relevant prior knowledge (Heitzmann et al., 2023; Richters et al., 2023; Stadler, Fischer, & Greiff, 2019).

Regulating the learning experience is another central purpose of learning activities in simulations. Regulation activities relate to the metacognitive and motivational-affective dimensions of learning, encompassing self-regulation activities, such as goal setting, planning, self-control, monitoring, and reflection (Azevedo, 2009; Bannert et al., 2014; Zimmerman, 1989). Through these activities, learners not only monitor and adapt their approach to learning tasks but may also modify the learning environment (e.g., learning support) to better suit their needs, given that the environment affords such flexibility. These regulating activities can become especially relevant when learners encounter an impasse in a simulation task, prompting them to reevaluate and adjust their strategies.

Social interaction and collaboration introduce an additional layer to task-processing and regulating activities that needs to be considered if simulated professional tasks are social by nature or if the design includes collaborative learning. For analyzing this collaborative dimension, frameworks specific to collaborative problem-solving (e.g., Chen, Wang, et al., 2018; Liu et al., 2016) suggest activities, such as sharing information, negotiating meaning, (co-)regulating collaboration, and initiating and maintaining interaction. These activities can help, for example, to identify a lack of information sharing in simulated professional collaboration (Radkowitsch et al., 2021).

3.2. What to personalize?

To address learners' prerequisites, processes, and activities, digital simulations can be enhanced through adaptive *learning support*, that is, measures that are adjusted to learner's individual differences and needs in order to facilitate the learning processes and outcomes. In the context of skill training, scaffolding and feedback stand out as fundamental learning support for guiding the acquisition of knowledge and skills and are, therefore, promising means for the personalization of simulation-based learning environments.

3.2.1. Scaffolding

Scaffolding structures and facilitates learners' processing of a learning task (e.g., a simulated situation) within their zone of proximal development—the zone of task difficulty where learners need guidance to succeed (Belland, 2014; Tabak & Kyza, 2018; Vygotsky, 1980; Wood et al., 1976). This zone is unique for every learner at a given point of time, emphasizing personalization as a central aspect of scaffolding. However, digital learning environments still often use hard scaffolding, offering static supports for anticipated learner difficulties (see Brush & Saye, 2002). In digital simulations, scaffolding can be implemented in different ways, through learning process and representational scaffolding.

Learning process scaffolding enhances learners' engagement in an effective learning process by offering additional instructional support beyond the core learning task's instruction (Fischer et al., 2022). Learning process scaffolding encompasses various forms (Chernikova, Heitzmann, Fink, et al., 2020; Sailer et al., 2024): worked and modeling examples for exemplifying appropriate task processing (Renkl, 2014; van Gog & Rummel, 2010); prompts and hints for directing attention to specific task elements (e.g., cognitive and metacognitive prompts; Bannert, 2009; Berthold et al., 2007; Martin et al., 2022, 2023; Quintana et al., 2004); scripts and roles for defining responsibilities and detailing task steps (e.g., collaboration scripts; Fischer et al., 2013; Vogel et al., 2017); and reflection phases for task evaluation (e.g., identifying goals and planning next steps) and self-assessment (Mamede & Schmidt, 2017). According to a meta-analysis, learning process scaffolds in digital learning environments improve cognitive outcomes in various contexts (Belland et al., 2017). In digital simulations, for example, knowledge activation prompts target relevant prior knowledge in long-term memory (Nickl, Sommerhoff, Radkowitsch, et al., 2024; Sommerhoff et al., 2023). Learning process scaffolding may also promote self-regulation activities, such as planning (Brydges et al., 2015; Lim et al., 2023; van der Graaf et al., 2023). Further, learning process scaffolding may aim to improve motivational-affective learning experiences (e.g., Farrell et al., 2024; Nickl, Sommerhoff, Böheim, et al., 2024) and boost collaborative learning through scripts that foster information sharing (e.g., assigning roles; Radkowitsch et al., 2021; Vogel et al., 2017).

Representational scaffolding, a second type of scaffolding in simulation-based learning, involves selecting and adjusting simulated practice representations to adapt the level of difficulty for learners with varying learning prerequisites (Fischer et al., 2022). Based on the approximation-of-practice approach (Grossman et al., 2009), it focuses on adjusting representational features of simulated cases or practice situations—namely, informational complexity, typicality, agency, and situation dynamics (Fischer et al., 2022): Complexity scaffolds manage informational complexity by adjusting the amount, interconnectedness, and salience of information (see Mamede et al., 2012; Stadler, Niepel, & Greiff, 2019). For example, making relevant case information relatively well identifiable might prevent cognitive overload for learners with limited prior knowledge (Chernikova et al., 2024; Farrell et al., 2024). Typicality scaffolds adjust the exemplarity or prototypicality of simulated situations (see Norman et al., 2007; Papa, 2016). For example, to facilitate the construction and restructuring of cognitive schemata (see KR–CP; Boshuizen et al., 2020), typical cases may be offered to novices and atypical cases to advanced learners. Agency scaffolds control the range of activities and the degree of self-regulation needed (Fischer et al., 2022); for example, for learners with lower metacognitive or social learning prerequisites, a simulated professional collaboration may focus only on few crucial professional social activities. Dynamics scaffolds modify the simulation's tempo and progression (see Stadler, Niepel, & Greiff, 2019), allowing, for example, to pause the simulation, potentially promoting metacognitive reflection, preventing cognitive overload, and reducing negative epistemic emotions. The effects of representational scaffolding are yet to be investigated empirically and systematically (Seidel et al., 2022). However, generally, simulations show large effects on higher education learning outcomes as shown in a meta-analysis (compared with small to medium effects of learning process scaffolding within simulations; Chernikova, Heitzmann, Stadler, et al., 2020)—suggesting great potential of purposefully designing simulated practice representations.

Dynamic personalization to learners' changing needs is a crucial aspect of scaffolding (referred to as contingency by Wood et al., 1976). Especially *fading*, which gradually reduces scaffolding until its removal (Collins et al., 1989), is considered a defining element of scaffolding (e.g., Belland, 2014; Pea, 2004). An example is the gradual fading of a complexity scaffold in the simulation, which progressively increases the informational complexity of the simulated situation to approximate real practice situations. Fading is also recommended to prevent the expertise reversal effect (Kalyuga et al., 2003), according to which scaffolds may even impede task processing and outcomes of advanced learners with higher task autonomy. An alternative approach is *cross-fading*, that is, transitioning from one scaffold to a qualitatively different scaffold, which provides less basic support, but instead targets more advanced task levels. A meta-analysis shows that high-guidance scaffolds (e.g., worked examples) benefit beginners, while advanced learners only benefit from scaffolding requiring some degree of self-regulation (especially reflection phases; Chernikova, Heitzmann, Fink, et al., 2020). The overall theory and empirical evidence thus suggest that personalizing scaffolding to each learner's prerequisites, learning processes, and activities is key in digital simulations for maximizing the benefits of this learning support.

3.2.2. *Feedback*

Instructional feedback offers evaluative information on intermediate or final outcomes of the learning task. It provides information about discrepancies between learners' current performance and learning goals, aiding in learners' success and failure assessment during knowledge application and skill development, such as in digital simulations (Sadler, 1989). Feedback is often divided into summative feedback, assessing goal achievement, and formative feedback, focusing on advice for improving learners' future task processing and learning progress (Black & Wiliam, 2009; Bloom et al., 1971; Lipnevich & Panadero, 2021). Hattie and Timperley (2007) conceptualize effective feedback as encompassing updates on current learning progress (feed back), references to the learning goals (feed up), and suggestions for improvement strategies (feed forward). According to this definition, effective feedback is adapted to learners' current prerequisites and learning processes, supporting learners' self-assessment and internal feedback mechanisms essential for simulation-based learning (Black & Wiliam, 2009; Heitzmann et al., 2023; Narciss, 2013; Nicol, 2021; Zimmerman, 1989).

Hattie and Timperley (2007) also identify four feedback content levels suited for learners with different prerequisites: Process level feedback gives detailed information and guidance on learners' task processing and is particularly beneficial for learners with low prior knowledge; self-regulation level feedback guides the learner's self-monitoring and self-regulation when they already achieved basic task understanding; task level feedback gives corrective performance information, for example, for advanced learners aiming to increase their task efficiency; and person level feedback expresses personal evaluations and affective responses, being uninformative for task learning but potentially serving motivational-affective purposes (Hattie & Timperley, 2007). In a synthesis of meta-analyses, Wisniewski et al. (2020) found that high-information feedback is generally more effective than simple corrective feedback, with larger effects on cognitive than motivational outcomes.

A previous synthesis of meta-analyses indicated that not only human but also computer-based feedback is effective for fostering cognitive outcomes (Hattie, 2008), however, its implementation varies considerably. Narciss et al. (2014) distinguished different types of feedback in digital learning environments (see also Sailer et al., 2024): Static feedback—which can be simple or elaborated—reveals the correct answer post-response, requiring minimal technical effort but lacking personalization (Attali, 2015; Bauer et al., 2025; Sailer et al., 2023). Simple adaptive feedback provides a summative assessment about the correctness of a learner's response at the task level (e.g., Stark et al., 2011). Elaborated adaptive feedback at the process level or self-regulation level is informed by a detailed analysis of learner's prerequisites, task processing, and outcomes—for example, to determine and explain where and why learners experienced difficulties in simulation-based learning. This type of feedback can be delivered by human instructors or computers using advanced data analysis techniques like natural language processing with deep learning techniques (Bauer et al., 2025; Cavalcanti et al., 2021; Sailer et al., 2023; Steinert et al., 2024). In line with the synthesis by Wisniewski et al. (2020), results of a meta-analysis indicate that in digital learning environments, elaborated forms of feedback are generally more effective than simple adaptive (knowledge of correctness of response) and static feedback (knowledge of correct response; der Kleij et al., 2015).

3.3. *Who personalizes?*

Personalization in learning can be achieved through computer or human agents, including learners or instructors (Chernikova et al., 2025; Kucirkova et al., 2021; Plass & Pawar, 2020). If adjustments to the learning environment are made through an instructor or a computer, after assessing relevant learner variables, this is referred to as *adaptivity*. In this form of personalization, the responsibility for adapting learner support can also be shared to varying degrees between human instructors and a computer (Fischer, 2001; Lee & Park, 2008; Molenaar, 2022; Plass & Pawar, 2020). In digital simulations, adaptivity is realized by using data on learner variables to adjust the amount, type, or timing of scaffolding or feedback according to learners' individual needs, such as providing worked examples for learners with low prior knowledge.

On the other hand, *adaptability* allows learners to modify their learning experience by regulating the amount, type, or timing of scaffolding and feedback to suit their preferences (Fischer, 2001; Lee & Park, 2008; Plass & Pawar, 2020). This allows learners to take ownership of their personalized learning experience (Walkington & Bernacki, 2018). Examples are offering learners hint buttons or a choice between cases of different difficulty levels. Offering learners autonomous control over their learning can enhance motivation and interest (Deci & Ryan, 2004; Ryan & Deci, 2000; Zimmerman & Moylan, 2009). However, learners might need adequate metacognitive prerequisites to assess their support needs, which can influence the effectiveness of adaptable learning support (Chernikova, Heitzmann, Stadler, et al., 2020; Lim et al., 2021; Yang & Stefaniak, 2023).

Support for human agents (learners and instructors) can come from computer systems, that accumulate and preprocess information on learning prerequisites, processes, and activities, helping to identify learners' struggles and suitable support measures. For example, monitoring processes of learners' performance may be facilitated through student-facing or teacher-facing dashboards (Jivet et al., 2017; Wiedbusch et al., 2021). In addition, learning environments can suggest suitable learning support, for example, through pop-up prompts guiding learners' task-processing, that can be switched off by learners (Chernikova et al., 2025). However, accurately assessing learner variables to optimally personalize the learning support remains a key challenge for both human and computer agents.

Although the present framework centers on the personalization of simulation-based learning from a learner's perspective, the role of teachers remains essential in shaping how personalization is implemented and experienced. Teachers are critical in designing or using simulations that align with educational goals, selecting or approving personalization strategies, and interpreting learner data when adaptive technologies fall short. As highlighted in recent work (Chernikova et al., 2025), instructional support in simulations is most effective when grounded in theoretically informed decisions about scaffolding and learner needs. Consequently, teachers need competencies not only in using simulations but also in understanding principles of adaptivity, learner modeling, and instructional support. These roles become even more relevant in AI-supported learning environments, where instructional decisions increasingly involve integrating automated guidance with human pedagogical judgment.

3.4. How to personalize?

To personalize learning support or display accumulated information to a human agent (e.g., via dashboards), computer systems create *learner models*. These models represent assumptions about a learner's (or a group of learners') current learning state, including their learning prerequisites, processes, activities, and predicted outcomes, for example, to optimize scaffolding and feedback in digital simulations. Learner models can be informed by a variety of data sources, from prior knowledge tests to multimodal indicators like self-reports, behavioral observations, or physiological data. The goal is to provide a basis for personalized instruction by identifying meaningful patterns in the data. The resulting estimate of an individual learner's current state, provided by a learner model based on a set of observed predispositions, results, or behaviors, then serves as an adjustment base for the personalization. While not always visible to learners or instructors, the transparency of learner models is subject to ethical discussions in learning analytics (Rosé et al., 2019).

3.4.1. Recording learner data

To effectively personalize instruction, it is essential to decide which learner data—indicating learning prerequisites, processes, activities, and outcomes—may be recorded and analyzed to construct learner models for tailoring learning support. The learner data can be assessed through capturing observable learning activities and additional measures that allow to infer latent learner variables. Traditionally, educational research has relied on tests (e.g., knowledge tests) and questionnaires (e.g., self-assessments of motivation or cognitive load) to assess learning prerequisites and processes. However, there's a growing trend toward employing a broader array of process-based data collection methods, including video, audio, text, logfile, eye tracking, and physiological measures, to get increasingly nuanced pictures of learners (Sailer et al., 2024). However, prioritization and necessity in collecting such diverse data for personalized simulation-based learning remain open questions due to the nascent state of research in this area. The potential risks associated with data collection, such as the psychological impact on learners of being constantly monitored, requires critical evaluation. Determining which types of data are most effective for specific learner characteristics, learning objectives, and learning contexts is still an open question that requires further systematic investigation. This critical evaluation is essential, as it will guide educators and developers in choosing the most pertinent and practical data collection methods without overwhelming the learning process with unnecessary complexity.

Additionally, adopting data minimization principles—collecting only the necessary amount of data for specific purposes and employing data anonymization techniques to protect learner identities—is an ethical imperative when transitioning from a research stage to the curricular implementation. Ensuring clear communication about the data recording and analysis practices and obtaining informed consent from learners upfront is crucial. Individual identities of the learners need to be protected as best as possible through privacy-enhancing technologies. Also, offering learners the ability to opt out of non-essential data recording without penalty is essential for maintaining control over their personal information.

When personalizing learning environments, the obtrusiveness of data collection methods is a key consideration. Frequent and intrusive assessments can disrupt learning continuity and might lead to learner fatigue, thereby negatively affecting the learning processes (e.g., motivational declines). For example, self-report measures might interrupt the learning flow, compared to less obtrusive methods, such as logfiles (Kovanovic et al., 2023; Sailer et al., 2024). Therefore, it is more promising to choose methods that integrate seamlessly into learning activities to maintain engagement and reduce learner burden (Rahimi & Shute, 2024). While the assessment of learning processes and activities is increasingly diversifying to include a variety of measures, the evaluation of learning prerequisites often still relies on tests and questionnaires. Such distinct assessments can be enhanced or even replaced through data from learners' previous learning tasks (e.g., interactions with simulations), if available, to reduce the burden of frequent testing.

In addition, the reliability, validity, and interpretability of the multimodal measurements are crucial for the successful personalization of digital learning environments (Ehlenz et al., 2022). Tests and questionnaires are typically optimized for reliability and validity; other data types, such as logfiles, offer relatively ambiguous insights (e.g., interpreting learning time as indicator for cognitive or motivational engagement) and require careful interpretation to ascertain their relevance to specific learner variables (Fan et al., 2022). These challenges can be addressed through robust theoretical frameworks, validation studies, and the triangulation of multimodal data to ensure meaningful personalization (Giannakos & Cukurova, 2023; Järvelä et al., 2021; Kovanovic et al., 2023; Molenaar et al., 2023; Olsen et al., 2020).

Cognitive learner variables can be assessed through verbal data, capturing knowledge integration in written reasoning (Sailer et al., 2023) and knowledge co-construction in dialogue (Dowell & Kovanović, 2022; Lippert et al., 2020; Nye et al., 2021). Logfile data, reflecting learners' interactions with digital simulations (e.g., page visits, click patterns, dwell time), can be analyzed regarding learners' task-processing activities to predict success in reasoning outcomes (Richters et al., 2023; Stadler, Fischer, & Greiff, 2019). Eye tracking offers insight into cognitive task processing (e.g., using fixation patterns; Kosel et al., 2021). Eye tracking metrics, such as pupil dilation are also used as indicators for cognitive load, especially in combination with other physiological measures, such as electrodermal activity, and self-assessment questionnaires (Appel et al., 2019; Ayres et al., 2021; Vanneste et al., 2021). Learners' prior knowledge is usually assessed with knowledge tests (e.g., Hofer et al., 2017; Lichtenberger et al., 2017). Such tests need to consider the situation-specific nature of professional knowledge, limiting the predictiveness of rather general knowledge tests (Kolovou et al., 2021; Stadler et al., 2021).

Metacognitive learner variables are critical in simulations demanding high degrees of self-regulation. Logfile analysis can reveal learners' self-regulation activities, such as planning, monitoring, and evaluating (Fan et al., 2021; Salehian Kia et al., 2023). These activities can also be inferred from verbal data (e.g., think-aloud; Lim et al., 2021; Raković et al., 2023), distinguishing between more and less successful learners based on their self-regulation activities. While the reliability and predictiveness of global metacognition questionnaires have been repeatedly questioned, more fine-grained self-report questionnaires offer nuanced insights into metacognitive behaviors (Greene & Azevedo, 2010; Rovers et al., 2019).

Motivational-affective learner variables during simulation-based learning can be identified through sentiment analysis in verbal data (Barrón-Estrada et al., 2017) or emotion detection via facial expressions recorded with web cameras (Greipl et al., 2021; Mangaroska et al., 2022; Taub et al., 2021), providing information about learners' affective states, such as confusion or joy (Frenzel et al., 2024). Behavioral indicators from logfiles may indicate learner motivation and volition (e.g., through learning time or number of responses; Motz et al., 2019). Also, physiological measures of arousal (e.g., electrodermal measures) have been explored as measures for motivational-affective states (Richter & Slade, 2017; Roos et al., 2021). Questionnaires can supplement these methods by offering learners' self-perceptions (e.g., Kron et al., 2021; Nickl, Sommerhoff, Böheim, et al., 2024).

Social learner variables are essential in simulations involving professional interactions or collaborative learning formats. Logfile data can be interpreted regarding the collaborative dimensions of task processing, such as information sharing and negotiating meaning (Liu et al., 2016; Richters et al., 2023). During collaborative simulation-based learning, eye tracking data on gaze similarity and electrodermal measures on physiological synchrony offer further understanding of group dynamics (Haataja et al., 2018; Olsen et al., 2020). Verbal data, such as written responses and dialogic chat or audio, can capture social learning processes and activities, aiding in the analysis of collaborative learning and simulated professional interaction (e.g., Vogel & Weinberger, 2018). Complementary tests and questionnaires can provide additional information, assessing knowledge and attitudes toward professional collaboration (e.g., Orchard et al., 2012).

3.4.2. Analyzing learner data

Creating learner models for personalized digital simulations critically depends on the analysis and integration of learner data, which necessitates employing computational data science methods, particularly from AI and machine learning domains. These methods are instrumental in detecting patterns within recorded learner data—especially if integrating multimodal indicators—and can be distinguished into different categories.

Supervised learning methods—such as linear regression, support vector machines, decision tree learning, random forests, or artificial neural networks—analyze labeled datasets (marked with specific attributes or categories) to establish patterns. These methods not only enhance the understanding of input-output relationships but also predict future outputs based on input data (Baker & Siemens, 2022; Bond et al., 2024; Chen et al., 2020; Du et al., 2021; Hilbert et al., 2021; James et al., 2021; Namoun & Alshanqiti, 2021; Sailer et al., 2024). For example, Richters et al. (2023) used support vector machines to predict learner success from task-processing activities in simulation logfiles. Pfeiffer et al. (2019) applied artificial neural networks for analyzing learners' written reasoning in simulation-based learning. Küchemann et al. (2020) compared different supervised learning methods for predicting physics task success using eye tracking data, finding a support vector machine to be most accurate. Appel et al. (2021) employed random forest classification to predict cognitive load from eye tracking metrics in a simulation game. Unsupervised learning methods—including methods for clustering, dimensionality reduction, and association rule mining techniques—focus on extracting patterns from unlabeled data (not marked with specific attributes or categories), identifying intrinsic structures without explicit output labels (Baker & Siemens, 2022; Sailer et al., 2024). For example, Nickl et al. (2022) and Radkowitsch et al. (2023) used latent profile analyses to cluster typical patterns of learning prerequisites and activities in simulation-based learning. To analyze collaborative knowledge construction based on audio-recorded group discussions, Ouyang et al. (2023) employed hidden Markov modeling, lag sequential analysis, and frequent sequence mining.

Positioned between supervised and unsupervised learning, semi-supervised learning integrates labeled and unlabeled data, for example, through techniques such as self-training and co-training, which are particularly valuable when acquiring comprehensive labeled data is challenging (James et al., 2021). Also, self-supervised learning is gaining prominence due to its ability to generate supervisory signals from the data itself without relying on external labels (Jaiswal et al., 2021). Moreover, reinforcement learning, which is inspired by behaviorist psychology, uses methods like Q-learning and deep reinforcement learning to refine strategies that enhance decision-making based on outcomes from prior interactions with the environment (van Otterlo & Wiering, 2012).

Well-known examples of self-supervised algorithms are found in the context of natural language processing, namely GPT (generative pre-trained transformers; Brown et al., 2020) and BERT (bidirectional encoder representations from transformers; Devlin et al., 2019). These large language models are pre-trained on vast text corpora using a language modeling objective, where the model learns to predict the next word in a sequence while considering the context. After pre-training, these models can be fine-tuned for specific tasks in a supervised learning manner, making them adaptable to various applications in the context of education (Kasneci et al., 2023; Tay et al., 2022). Considering data protection regulations, alternatives consist in fine-tuning smaller open-access models that can be hosted on regulated servers (Kasneci et al., 2023). Beyond large language models, multimodal foundation models, such as CLIP (contrastive language-image pre-training; Radford et al., 2021) and ViLBERT (vision-and-language BERT; Lu et al., 2019), represent a significant advancement in integrating diverse data types. These models are trained on extensive datasets comprising both text and images, employing objectives that enable them to understand and generate predictions across modalities. Once pre-trained, these models can be fine-tuned for tasks, such as visual question answering and cross-modal information retrieval, marking a significant progress toward comprehensive AI systems that can be very useful in educational contexts (Küchemann et al., 2024). Using multimodal models, digital learning environments, such as digital simulations, can personalize learning support based on learner data integrated from multiple sources of different modalities, such as dialogue and eye tracking data.

However, choosing the right analytical approach involves balancing prediction accuracy with model interpretability. While deep learning methods offer high accuracy, their complexity may obscure interpretability, raising critical concerns about the potential for bias and misinterpretation. In particular, biases in machine learning models can perpetuate or even exacerbate existing disparities when used in educational settings, requiring thorough examination and adjustment. Therefore, transparent methods, such as regression analyses, maintain their value not only for their clarity but also for easier validation against ethical standards and bias mitigation (Hilbert et al., 2021; James et al., 2021; Sailer et al., 2024). Integrating different methodologies enriches personalization strategies in digital simulations and enhances the comprehension of relationships between learner variables in accompanying educational research (Kitto et al., 2023).

Furthermore, handling learners' data privacy in digital simulations that potentially record and analyze a wide variety of learner data for personalized learning is a key concern. Ensuring data privacy becomes especially complex when employing advanced data analysis techniques, which might utilize sensitive or multifaceted learner data. Accompanying the educational and technological developments of personalized digital simulations for higher education with developments of strategies to safeguard learner data is essential to ensure trust and security in these educational technologies. This involves adhering to data protection regulations and implementing robust privacy measures to protect learners' information from misuse or unauthorized access, as well as continually auditing and updating these measures to address new privacy challenges as they arise.

3.5. When to personalize?

A crucial aspect of personalization strategies in digital simulations is the time scale used for updating learner models that make decisions about personalized learning support. A *macro-level personalization* strategy builds on infrequent measurements of learner data (e.g., prior knowledge tests) to assign learners to groups receiving different learning support (e.g., Johnson et al., 2014), such as types of scaffolds. However, such personalization cannot account for short-term changes in learner variables, such as those occurring between or within individual simulation cases (Tetzlaff et al., 2021). With a *meso-level personalization* strategy, the learner model is updated after learners complete a significant segment of the simulation—such as one of multiple simulated practice representations—based on the learner data accumulated during this segment (Tetzlaff et al., 2021). Meso-level personalization, for instance, could involve adjusting the difficulty level of subsequent practice representations based on the learner's performance in earlier ones. This approach, however, still overlooks changes in learner variables occurring within individual practice representations. The *micro-level personalization* strategy considers changes within smaller learning segments, such as individual practice representations (Tetzlaff et al., 2021). This requires a real-time analysis of learner variables to infer dynamic learning prerequisites or processes (e.g., Stadler, Fischer, & Greiff, 2019), for example, to offer immediate hints and prompts based on learners' task processing.

The three personalization strategies differ in the frequency with which changes in the need for learning support are checked. It is plausible to assume that the effectiveness of the personalization strategy depends on the stability or volatility of the supported learner variables (Tetzlaff et al., 2021). For example, motivational or emotional learning processes may fluctuate rapidly, making personalization based on a meso-level or micro-level strategy potentially more effective than a macro-level strategy. However, cognitive and metacognitive processes are also likely to benefit from a higher frequency of personalization due to their dependence on motivational–affective processes, as well as contextual variables. In contrast, higher stability is assumed for general cognitive abilities. However, there has hardly been any systematic research on the extent to which an increase in the frequency of personalization of scaffolding and feedback (i.e., at the meso-level and micro-level) is superior to less frequent personalization (i.e., at the macro-level).

4. The road ahead: Research on personalized digital simulations in higher education

In this paper, we have outlined the SHARP framework (see Fig. 1) as a starting point for advancing both foundational and applied research on personalized simulation-based learning in higher education. To enhance the framework's practicality and theoretical robustness, the effectiveness of the proposed personalization approach requires further empirical validation. Systematic empirical studies are essential, especially to better understand the relationships between different learner characteristics and how to select and apply the best methodologies for recording and analyzing related data. Second, the technical integration of advanced AI and machine learning technologies can pose challenges, including costs as well as development and maintenance demands, which could hinder widespread adoption. Furthermore, while the paper acknowledges the importance of data privacy and ethical considerations, more detailed strategies need to be developed to mitigate risks associated with extensive data collection and analysis, ensuring robust protection of learner's privacy. Lastly, the generalizability of the framework across diverse educational settings remains to be explored across various learner groups and institutional contexts. These limitations underscore the necessity for future research to validate and refine the SHARP framework, ensuring it is explanatory, effective, and ethically sound.

The SHARP framework can guide this research endeavors by structuring (1) the generation and refinement of research questions and hypotheses that may be systematically investigated by (2) interdisciplinary research collaborations for developing design principles for personalized simulation-based learning in higher education. (1) merging research directions include: (a) understanding learner profiles by investigating interactions of learning prerequisites, processes, activities, and outcomes; (b) examining effects of personalization through various scaffolding and feedback approaches, especially the effects and synergies of representational scaffolding; (c) analyzing the differential effects and synergies of adaptivity and adaptability, as well as their synergies with teacher support, while taking into account learners' characteristics such as their self-regulation; (d) addressing technological challenges (e.g., integration of multimodal data) as well as privacy concerns and other ethical considerations in data recording and analysis; (e) investigating the effectiveness of different personalization strategies (e.g., at the micro-level) for adapting to learner variables of varying stability or volatility; and (f) testing the generalizability of effects across professional fields.

Future research may prioritize enhancing our understanding of how to systematically address individual differences among learners through personalization, focusing on the various learner variables that are crucial for acquiring knowledge and skills with simulations. As outlined in our framework, relevant learner characteristics include individual differences in cognitive, metacognitive, motivational-affective, and social prerequisites, as well as in the related learning processes and activities in a simulation. Future studies may investigate which data—such as pre-simulation diagnostics, learner input, or interaction data—are most indicative for these dimensions and how they can best inform personalization strategies in a targeted and theoretically grounded manner. Furthermore, research may explore how personalized simulations might not only adapt to learners' current characteristics but also support the development of effective learning processes such as self- or co-regulation over time. Additionally, future research might explore how teachers can be meaningfully involved in co-designing and facilitating personalized simulations and what kinds of professional development are needed to support this role. (2) Addressing these directions requires a comprehensive framework, integrating conceptual, methodological, and technical foundations (Heitzmann et al., 2021), as outlined in this paper. The SHARP framework may facilitate collaborative research across educational science, psychology, computer science, and relevant professional fields like medical and teacher education. Such interdisciplinary projects may examine conditions for effective personalized simulations, exploit methodological synergies between different areas of expertise, establish effective data science infrastructures for personalization, and synthesize data and findings across studies and projects (Fink et al., 2021). Research might also address how to integrate the findings into higher education practice, for example, by identifying knowledge and resources needed by higher education teachers. Moreover, qualifying a new generation of interdisciplinary educational researchers that is data science savvy and aware of privacy concerns is essential to keep pace with AI and educational technology advancements. This research may offer transformative perspectives on learning in higher education, possibly enhancing engagement and effectiveness through personalized simulations. In this context, the SHARP framework seeks to bridge theoretical concepts with methodological and technical approaches, calling for comprehensive interdisciplinary research to advance learning through personalized digital simulations in higher education.

CRediT authorship contribution statement

Elisabeth Bauer: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Nicole Heitzmann:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Maria Bannert:** Writing – review & editing, Conceptualization. **Olga Chernikova:** Writing – review & editing, Conceptualization. **Martin R. Fischer:** Writing – review & editing, Conceptualization. **Anne C. Frenzel:** Writing – review & editing, Conceptualization. **Martin Gartmeier:** Writing – review & editing, Conceptualization. **Sarah I. Hofer:** Writing – review & editing, Conceptualization. **Doris Holzberger:** Writing – review & editing, Conceptualization. **Enkelejda Kasneci:** Writing – review & editing, Conceptualization. **Jenna Koenen:** Writing – review & editing, Conceptualization. **Christian Kosel:** Writing – review & editing, Conceptualization. **Stefan Küchemann:** Writing – review & editing, Conceptualization. **Jochen Kuhn:** Writing – review & editing, Conceptualization. **Tilman Michaeli:** Writing – review & editing, Conceptualization. **Birgit J. Neuhaus:** Writing – review & editing, Conceptualization. **Frank Niklas:** Writing – review & editing, Conceptualization. **Andreas Obersteiner:** Writing – review & editing, Conceptualization. **Jürgen Pfeffer:** Writing – review & editing, Conceptualization. **Michael Sailer:** Writing – review & editing, Conceptualization. **Ralf Schmidmaier:** Writing – review & editing, Conceptualization. **Bernhard Schmidt-Hertha:** Writing – review & editing, Conceptualization. **Matthias Stadler:** Writing – review & editing, Conceptualization. **Stefan Ufer:** Writing – review & editing, Conceptualization. **Andreas Vorholzer:** Writing – review & editing, Conceptualization. **Tina Seidel:** Writing – review & editing, Writing – original draft, Visualization, Funding acquisition, Conceptualization. **Frank Fischer:** Writing – review & editing, Writing – original draft, Visualization, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT 4 in order to revise the draft for readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

Elisabeth Bauer is a guest editor for the special issue for which this article was submitted. In addition, Michael Sailer is a guest editor for the special issue and the current special issue editor of the journal. Appropriate measures were taken to ensure that the editorial process remained objective and unaffected by these roles.

Acknowledgements

This research was supported by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG SHARP TRR419/1).

References

Aleven, V., McLaughlin, E. A., Glenn, R. A., & Koedinger, K. R. (2017). Instruction based on adaptive learning technologies. In R. E. Mayer, & P. Alexander (Eds.), *Handbook of research on learning and instruction* (2nd ed., pp. 522–560). Routledge.

Amiel, J. M., Andriole, D. A., Biskobing, D. M., Brown, D. R., Cutrer, W. B., Emery, M. T., … Association of American Medical Colleges Core EPAs for Entering Residency Pilot Team. (2021). Revisiting the Core Entrustable professional activities for entering residency. *Academic Medicine: Journal of the Association of American Medical Colleges, 96*(7S), S14–S21. https://doi.org/10.1097/ACM.0000000000004088

Appel, T., Gerjets, P., Hoffmann, S., Moeller, K., Ninaus, M., Scharinger, C., … Kasneci, E. (2021). Cross-task and cross-participant classification of cognitive load in an emergency simulation game. *IEEE Transactions on Affective Computing, 14*(2), 1558–1571. https://doi.org/10.1109/TAFFC.2021.3098237

Appel, T., Sevcenko, N., Wortha, F., Tsarava, K., Moeller, K., Ninaus, M., … Gerjets, P. (2019). Predicting cognitive load in an emergency simulation based on behavioral and physiological measures. *International Conference on Multimodal Interaction, 2019*, 154–163. https://doi.org/10.1145/3340555.3353735

Attali, Y. (2015). Effects of multiple-try feedback and question type during mathematics problem solving on performance in similar problems. *Computers & Education, 86*, 260–267. https://doi.org/10.1016/j.compedu.2015.08.011

Ayres, P., Lee, J. Y., Paas, F., & van Merriënboer, J. J. G. (2021). The validity of physiological measures to identify differences in intrinsic cognitive load. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.702538

Azevedo, R. (2009). Theoretical, conceptual, methodological, and instructional issues in research on metacognition and self-regulated learning: A discussion. *Metacognition and Learning, 4*(1), 87–95. https://doi.org/10.1007/s11409-009-9035-7

Baker, R. S., & Siemens, G. (2022). Learning analytics and educational data mining. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (3rd ed., pp. 259–278). Cambridge University Press. https://doi.org/10.1017/9781108888295.016.

Bandura, A. (2008). *Observational learning.* In The International Encyclopedia of Communication: John Wiley & Sons, Ltd.. https://doi.org/10.1002/9781405186407.wbieco004

Bannert, M. (2009). Promoting self-regulated learning through prompts. *Zeitschrift Für Pädagogische Psychologie, 23*(2), 139–145. https://doi.org/10.1024/1010-0652.23.2.139

Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning, 9*(2), 161–185. https://doi.org/10.1007/s11409-013-9107-6

Barrón-Estrada, M. L., Zatarain-Cabada, R., Oramas-Bustillos, R., & González-Hernández, F. (2017). Sentiment analysis in an affective intelligent tutoring system. In *2017 IEEE 17th international conference on advanced learning technologies (ICALT)* (pp. 394–397). https://doi.org/10.1109/ICALT.2017.137

Bauer, E., Fischer, F., Kiesewetter, J., Shaffer, D. W., Fischer, M. R., Zottmann, J. M., & Sailer, M. (2020). Diagnostic activities and diagnostic practices in medical education and teacher education: An interdisciplinary comparison. *Frontiers in Psychology, 11*, 2787. https://doi.org/10.3389/fpsyg.2020.562665

Bauer, E., Sailer, M., Kiesewetter, J., Fischer, M. R., & Fischer, F. (2022). Diagnostic argumentation in teacher education: Making the case for justification, disconfirmation, and transparency. *Frontiers. Education, 7, Article 977631*. https://doi.org/10.3389/feduc.2022.977631

Bauer, E., Sailer, M., Niklas, F., Greiff, S., Sarbu-Rothsching, S., Zottmann, J. M., & Fischer, F. (2025). AI-based adaptive feedback in simulations for teacher education: An experimental replication in the field. *Journal of Computer Assisted Learning, 41*(1), Article e13123. https://doi.org/10.1111/jcal.13123

Behling, F., Förtsch, C., & Neuhaus, B. J. (2022). The refined consensus model of pedagogical content knowledge (PCK): Detecting filters between the realms of PCK. *Education Sciences, 12*(9), 1–21. https://doi.org/10.3390/educsci12090592

Belland, B. R. (2014). Scaffolding: Definition, current debates, and future directions. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 505–518). Springer. https://doi.org/10.1007/978-1-4614-3185-5_39.

Belland, B. R., Walker, A. E., Kim, N. J., & Lefler, M. (2017). Synthesizing results from empirical research on computer-based scaffolding in STEM education: A Meta-analysis. *Review of Educational Research, 87*(2), 309–344. https://doi.org/10.3102/0034654316670999

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? *Educational Psychology Review, 33*(4), 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

Bernacki, M. L., & Walkington, C. (2018). The role of situational interest in personalized learning. *Journal of Educational Psychology, 110*(6), 864–881. https://doi.org/10.1037/edu0000250

Berndt, M., Schmidt, F. M., Sailer, M., Fischer, F., Fischer, M. R., & Zottmann, J. M. (2021). Investigating statistical literacy and scientific reasoning & argumentation in medical-, social sciences-, and economics students. *Learning and Individual Differences, 86*, Article 101963. https://doi.org/10.1016/j.lindif.2020.101963

Berthold, K., Nückles, M., & Renkl, A. (2007). Do learning protocols support learning strategies and outcomes? The role of cognitive and metacognitive prompts. *Learning and Instruction, 17*(5), 564–577. https://doi.org/10.1016/j.learninstruc.2007.09.007

Bichler, S., Schwaighofer, M., Stadler, M., Bühner, M., Greiff, S., & Fischer, F. (2020). How working memory capacity and shifting matter for learning with worked examples—A replication study. *Journal of Educational Psychology, 112*(7), 1320–1337. https://doi.org/10.1037/edu0000433

Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability, 21*(1), 5–31. https://doi.org/10.1007/s11092-008-9068-5

Blömeke, S., Gustafsson, J.-E., & Shavelson, R. J. (2015). Beyond dichotomies: Competence viewed as a continuum. *Zeitschrift für Psychologie, 223*(1), 3–13. https://doi.org/10.1027/2151-2604/a000194

Bloom, B. S., Hastings, J. T., & Madaus, G. F. (1971). *Handbook on formative and summative evaluation of student learning*. New York: McGraw-Hill. http://archive.org/details/handbookonformat00bloo.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., … Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education, 21*(1), 4. https://doi.org/10.1186/s41239-023-00436-z

Boshuizen, H. P. A., Gruber, H., & Strasser, J. (2020). Knowledge restructuring through case processing: The key to generalise expertise development theory across domains? *Educational Research Review, 29*, Article 100310. https://doi.org/10.1016/j.edurev.2020.100310

Braun, L. T., et al. (2019). Scaffolding clinical reasoning of medical students with virtual patients: Effects on diagnostic accuracy, efficiency, and errors. *Diagnosis, 6*(2), 137–149. https://doi.org/10.1515/dx-2018-0090

Bromme, R., & Tillema, H. (1995). Fusing experience and theory: The structure of professional knowledge. *Learning and Instruction, 5*(4), 261–267. https://doi.org/10.1016/0959-4752(95)00018-6

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., … Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901. https://papers.nips.cc/paper/2020/hash/1457c0d6bfcb4967418bfb8ac142f64a-Abstract.html.

Brush, T., & Saye, J. W. (2002). A summary of research exploring hard and soft scaffolding for teachers and students using a multimedia supported learning environment. *The Journal of Interactive Online Learning, 1*(2). https://www.semanticscholar.org/paper/A-Summary-of-Research-Exploring-Hard-and-Soft-for-a-Brush-Saye/9c857a2106946d6fdae5de29ad3819078fe42da1.

Brydges, R., Manzone, J., Shanks, D., Hatala, R., Hamstra, S. J., Zendejas, B., & Cook, D. A. (2015). Self-regulated learning in simulation-based training: A systematic review and meta-analysis. *Medical Education, 49*(4), 368–378. https://doi.org/10.1111/medu.12649

Cavalcanti, A. P., Barbosa, A., Carvalho, R., Freitas, F., Tsai, Y.-S., Gašević, D., & Mello, R. F. (2021). Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence, 2*, Article 100027. https://doi.org/10.1016/j.caeai.2021.100027

Chen, J., Wang, M., Kirschner, P. A., & Tsai, C.-C. (2018). The role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A Meta-analysis. *Review of Educational Research, 88*(6), 799–843. https://doi.org/10.3102/0034654318791584

Chen, O., Castro-Alonso, J. C., Paas, F., & Sweller, J. (2018). Extending cognitive load theory to incorporate working memory resource depletion: Evidence from the spacing effect. *Educational Psychology Review, 30*(2), 483–501. https://doi.org/10.1007/s10648-017-9426-2

Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1*, Article 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chernikova, O., Heitzmann, N., Fink, M., Timothy, V., Seidel, T., & Fischer, F. (2020). Facilitating diagnostic competences in higher education—A Meta-analysis in medical and teacher education. *Educational Psychology Review, 32*(1), 157–196.

Chernikova, O., Heitzmann, N., Stadler, M., Holzberger, D., Seidel, T., & Fischer, F. (2020). Simulation-based learning in higher education: A Meta-analysis. *Review of Educational Research, 90*(4), 499–541. https://doi.org/10.3102/0034654320933544

Chernikova, O., Holzberger, D., Heitzmann, N., Stadler, M., Seidel, T., & Fischer, F. (2024). Where salience goes beyond authenticity. *Zeitschrift Für Pädagogische Psychologie, 38*(1–2), 15–25. https://doi.org/10.1024/1010-0652/a000357

Chernikova, O., Sommerhoff, D., Stadler, M., Holzberger, D., Nickl, M., Seidel, T., … Heitzmann, N. (2025). Personalization through adaptivity or adaptability? A meta-analysis on simulation-based learning in higher education. *Educational Research Review, 46*, Article 100662. https://doi.org/10.1016/j.edurev.2024.100662

Collins, A., Brown, J. S., & Newman, S. E. (1989). Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics. In L. B. Resnick (Ed.), *Knowing, learning, and instruction: Essays in honor of Robert Glaser* (pp. 453–494). Lawrence Erlbaum Associates, Inc.

Cook, D. A., et al. (2012). Comparative effectiveness of technology-enhanced simulation versus other instructional methods: A systematic review and meta-analysis. *Simulation in Healthcare, 7*(5), 308–320. https://doi.org/10.1097/SIH.0b013e3182614f95

Dai, C.-P., & Ke, F. (2022). Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review. *Computers and Education: Artificial Intelligence, 3*, Article 100087. https://doi.org/10.1016/j.caeai.2022.100087

Deci, E. L., & Ryan, R. M. (2004). *Handbook of self-determination research*. University Rochester Press.

Kleij, F. M. V., der, Feskens, R. C. W., & Eggen, T. J. H. M. (2015). Effects of feedback in a computer-based learning environment on students' learning outcomes A Meta-analysis. *Review of Educational Research, 0034654314564881*. https://doi.org/10.3102/0034654314564881

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of deep bidirectional transformers for language understanding* (arXiv:1810.04805). arXiv. https://doi.org/10.48550/arXiv.1810.04805.

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*(2), 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001

Dowell, N., & Kovanović, V. (2022). Modeling educational discourse with natural language processing. In C. Lang, G. Siemens, & A. F. Wise (Eds.), *The handbook of learning analytics* (2nd ed., pp. 105–119). https://doi.org/10.18608/hla22.011 Vol.

Du, X., Yang, J., Shelton, B. E., Hung, J.-L., & Zhang, M. (2021). A systematic meta-review and analysis of learning analytics research. *Behaviour & Information Technology, 40*(1), 49–62. https://doi.org/10.1080/0144929X.2019.1669712

Dubovi, I., & Tabak, I. (2020). An empirical analysis of knowledge co-construction in YouTube comments. *Computers & Education, 156*, Article 103939. https://doi.org/10.1016/j.compedu.2020.103939

Ehlenz, M. S., Heinemann, B., & Schroeder, U. (2022). Information sources and their potential for multimodal learning analytics in laboratory-based learning. In D. Uckelmann, G. Romagnoli, J. Baalsrud Hauge, & V. Kammerlohr (Eds.), *Online-labs in education* (pp. 139–152). Nomos Verlagsgesellschaft GmbH & Co. KG. https://doi.org/10.5771/9783957104106-139.

Engelmann, K., & Bannert, M. (2021). Analyzing temporal data for understanding the learning process induced by metacognitive prompts. *Learning and Instruction, 72*, Article 101205. https://doi.org/10.1016/j.learninstruc.2019.05.002

Fan, Y., Saint, J., Singh, S., Jovanovic, J., & Gašević, D. (2021). A learning analytic approach to unveiling self-regulatory processes in learning tactics. *LAK21: 11th international learning analytics and knowledge conference*, 184–195. https://doi.org/10.1145/3448139.3448211

Fan, Y., van der Graaf, J., Lim, L., Raković, M., Singh, S., Kilgour, J., Moore, J., Molenaar, I., Bannert, M., & Gašević, D. (2022). Towards investigating the validity of measurement of self-regulated learning based on trace data. *Metacognition and Learning, 17*(3), 949–987. https://doi.org/10.1007/s11409-022-09291-1

Fariani, R. I., Junus, K., & Santoso, H. B. (2023). A systematic literature review on personalised learning in the higher education context. *Technology, Knowledge and Learning, 28*(2), 449–476. https://doi.org/10.1007/s10758-022-09628-4

Farrell, M., Martin, M., Böheim, R., Renkl, A., Rieß, W., Könings, K. D., & Van Merrienboer, J. (2024). Signaling cues and focused prompts for professional vision support: The interplay of instructional design and situational interest in preservice teachers' video analysis. *Instructional Science, 52*(6), 879–917. https://doi.org/10.1007/s11251-024-09662-y

Fink, M. C., Radkowitsch, A., Bauer, E., Sailer, M., Kiesewetter, J., Schmidmaier, R., & Fischer, M. R. (2021). Simulation research and design: A dual-level framework for multi-project research programs. *Educational Technology Research and Development, 69*, 809–841. https://doi.org/10.1007/s11423-020-09876-0

Fischer, F., Bauer, E., Seidel, T., Schmidmaier, R., Radkowitsch, A., Neuhaus, B. J., … Fischer, M. R. (2022). Representational scaffolding in digital simulations – Learning professional practices in higher education. *Information and Learning Science, 123*(11/12), 645–665. https://doi.org/10.1108/ILS-06-2022-0076

Fischer, F., Kollar, I., Stegmann, K., & Wecker, C. (2013). Toward a script theory of guidance in computer-supported collaborative learning. *Educational Psychologist, 48*(1), 56–66.

Fischer, F., Kollar, I., Ufer, S., Sodian, B., Hussmann, H., Pekrun, R., … Eberle, J. (2014). Scientific reasoning and argumentation: Advancing an interdisciplinary research agenda in education. *Frontline Learning Research, 2*(2), 28–45.

Fischer, G. (2001). User Modeling in Human–Computer Interaction. *User Modeling and User-Adapted Interaction, 11*(1), 65–86. https://doi.org/10.1023/A:1011145532042

Floden, R., Stephens, A., & Scherer, L. (Eds.). (2020). *Changing expectations for the K-12 teacher workforce: Policies, preservice education, professional development, and the workplace*. National Academies Press. https://doi.org/10.17226/25603.

Förtsch, C., Sommerhoff, D., Fischer, F., Fischer, M. R., Girwidz, R., Obersteiner, A., … Neuhaus, B. J. (2018). Systematizing professional knowledge of medical doctors and teachers: Development of an interdisciplinary framework in the context of diagnostic competences. *Education Sciences, 8*(4), 207. https://doi.org/10.3390/educsci8040207

Frank, J. R., Snell, L. S., Cate, O. T., Holmboe, E. S., Carraccio, C., Swing, S. R., … Harris, K. A. (2010). Competency-based medical education: Theory to practice. *Medical Teacher, 32*(8), 638–645. https://doi.org/10.3109/0142159X.2010.501190

Frenzel, A. C., Dindar, M., Pekrun, R., Reck, C., & Marx, A. K. G. (2024). Joy is reciprocally transmitted between teachers and students: Evidence on facial mimicry in the classroom. *Learning and Instruction, 91*, Article 101896. https://doi.org/10.1016/j.learninstruc.2024.101896

Gartmeier, M., Bauer, J., Fischer, M. R., Hoppe-Seyler, T., Karsten, G., Kiessling, C., … Prenzel, M. (2015). Fostering professional communication skills of future physicians and teachers: Effects of E-learning with video cases and role-play. *Instructional science: An international. Journal of the Learning Sciences, 43*(4), 443–462 (eric).

Gegenfurtner, A., Gruber, H., Holzberger, D., Keskin, Ö., Lehtinen, E., Seidel, T., … Säljö, R. (2023). Towards a cognitive theory of visual expertise: Methods of inquiry. In *Re-theorising learning and research methods in learning research*. Routledge.

Gegenfurtner, A., Quesada-Pallarès, C., & Knogler, M. (2014). Digital simulation-based training: A meta-analysis. *British Journal of Educational Technology, 45*(6), 1097–1114.

Gemini Team Google, Anil, R., Borgeaud, S., Wu, Y., Alayrac, J.-B., Yu, J., … Vinyals, O. (2023). Gemini: A Family of Highly Capable Multimodal Models. arXiv:2312.11805 *arXiv*. https://doi.org/10.48550/arXiv.2312.11805.

Ghanem, C., Kollar, I., Fischer, F., Lawson, T. R., & Pankofer, S. (2018). How do social work novices and experts solve professional problems? A micro-analysis of epistemic activities and the use of evidence. *European Journal of Social Work, 21*(1), 3–19. https://doi.org/10.1080/13691457.2016.1255931

Gherardi, S. (2009). Introduction: The critical power of the `practice Lens. *Management Learning, 40*(2), 115–128. https://doi.org/10.1177/1350507608101225

Giannakos, M., & Cukurova, M. (2023). The role of learning theory in multimodal learning analytics. *British Journal of Educational Technology, 54*(5), 1246–1267. https://doi.org/10.1111/bjet.13320

Goodwin, C. (1994). Professional Vvsion. *American Anthropologist, 96*(3), 606–633. https://doi.org/10.1525/aa.1994.96.3.02a00100

Greene, J. A., & Azevedo, R. (2010). The measurement of learners' self-regulated cognitive and metacognitive processes while using computer-based learning environments. *Educational Psychologist, 45*(4), 203–209. https://doi.org/10.1080/00461520.2010.515935

Greipl, S., Bernecker, K., & Ninaus, M. (2021). Facial and bodily expressions of emotional engagement: How dynamic measures reflect the use of game elements and subjective experience of emotions and effort. *Proceedings of the ACM on human-computer interaction, 5(CHI PLAY), 240*(1–240), 25. https://doi.org/10.1145/3474667

Grossman, P. (2021). *Teaching Core practices in teacher education*. Harvard Education Press.

Grossman, P., Compton, C., Igra, D., Ronfeldt, M., Shahan, E., & Williamson, P. (2009). Teaching practice: A cross-professional perspective. *Teachers College Record, 111*(9), 2055–2100.

Haataja, E., Malmberg, J., & Järvelä, S. (2018). Monitoring in collaborative learning: Co-occurrence of observed behavior and physiological synchrony explored. *Computers in Human Behavior, 87*, 337–347. https://doi.org/10.1016/j.chb.2018.06.007

Hamstra, S. J., Brydges, R., Hatala, R., Zendejas, B., & Cook, D. A. (2014). Reconsidering Fidelity in simulation-based training. *Academic Medicine, 89*(3), 387. https://doi.org/10.1097/ACM.0000000000000130

Hardy, I., Decristan, J., & Klieme, E. (2019). Adaptive teaching in research on learning and instruction. *Journal for Educational Research Online, 11*(2), 169–191.

Hattie, J. (2008). Visible learning: A synthesis of over 800 Meta-analyses relating to achievement. *Routledge*. https://doi.org/10.4324/9780203887332

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112.

Heitzmann, N., Opitz, A., Stadler, M., Sommerhoff, D., Fink, M. C., Obersteiner, A., … Fischer, F. (2021). Cross-disciplinary research on learning and instruction – Coming to terms. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.562658

Heitzmann, N., Seidel, T., Opitz, A., Hetmanek, A., Wecker, C., Fischer, M., … Fischer, F. (2019). Facilitating diagnostic competences in simulations in higher education. *Frontline Learning Research, 7*(4), 1–24. https://doi.org/10.14786/flr.v7i4.384

Heitzmann, N., Stadler, M., Richters, C., Radkowitsch, A., Schmidmaier, R., Weidenbusch, M., & Fischer, M. R. (2023). Learners' adjustment strategies following impasses in simulations—Effects of prior knowledge. *Learning and Instruction, 83*, Article 101632. https://doi.org/10.1016/j.learninstruc.2022.101632

Hetmanek, A., Engelmann, K., Opitz, A., & Fischer, F. (2018). *Beyond intelligence and domain knowledge: Scientific reasoning and argumentation as a set of cross-domain skills*. In Scientific Reasoning and Argumentation: Routledge.

Hidi, S., & Renninger, K. A. (2006). The four-phase model of interest development. *Educational Psychologist, 41*(2), 111–127. https://doi.org/10.1207/s15326985ep4102_4

Hilbert, S., Coors, S., Kraus, E., Bischl, B., Lindl, A., Frei, M., Wild, J., Krauss, S., Goretzko, D., & Stachl, C. (2021). Machine learning for the educational sciences. *Review of Education, 9*(3), Article e3310. https://doi.org/10.1002/rev3.3310

Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*(3), 235–266.

Hofer, S. I., Schumacher, R., & Rubin, H. (2017). The test of basic mechanics conceptual understanding (bMCU): Using Rasch analysis to develop and evaluate an efficient multiple choice test on Newton's mechanics. *International Journal of STEM Education, 4*(1), 18. https://doi.org/10.1186/s40594-017-0080-5

Holzberger, D., Brandl, L., Stadler, M., Obersteiner, A., Chernikova, O., Pickal, A. J., Nickl, M., Richters, C., Kron, S., Wecker, C., Heitzmann, N., Irmer, M., Corves, C., Radkowitsch, A., Neuhaus, B. J., Fischer, M. R., Ufer, S., Fischer, F., Sommerhoff, D., & Seidel, T. (2024). Fostering Diagnostic Competences in Simulation-Based Learning Environments: An Individual Participant Data Meta-Analysis on the Interplay between Expectancy Beliefs and Task Value. *Registered Report in Journal of Educational Psychology*. in-principle accepted.

Huber, S. A., Häusler, J., Jurik, V., & Seidel, T. (2015). Self-underestimating students in physics instruction: Development over a school year and its connection to internal learning processes. *Learning and Individual Differences, 43*, 83–91. https://doi.org/10.1016/j.lindif.2015.08.021

Irmer, M., Traub, D., & Neuhaus, B. J. (2024). Fostering ePCK in pre-service biology teacher education using adaptive scaffolding in a video-based simulation. *Cogent education, 11*(1). https://doi.org/10.1080/2331186X.2024.2422272. article 2422272.

Jaiswal, A., Babu, A. R., Zadeh, M. Z., Banerjee, D., & Makedon, F. (2021). A survey on contrastive self-supervised learning. *Technologies, 9*(1). https://doi.org/10.3390/technologies9010002. Article 1.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An introduction to statistical learning: With applications in R* (2nd ed. 2021 ed.). Springer.

Jarodzka, H., van Gog, T., Dorr, M., Scheiter, K., & Gerjets, P. (2013). Learning to see: Guiding students' attention via a model's eye movements fosters learning. *Learning and Instruction, 25*, 62–70. https://doi.org/10.1016/j.learninstruc.2012.11.004

Järvelä, S., Järvenoja, H., & Malmberg, J. (2019). Capturing the dynamic and cyclical nature of regulation: Methodological Progress in understanding socially shared regulation in learning. *International Journal of Computer-Supported Collaborative Learning, 14*(4), 425–441. https://doi.org/10.1007/s11412-019-09313-2

Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., & Kirschner, P. A. (2021). What multimodal data can tell us about the students' regulation of their learning process? *Learning and Instruction, 72*, Article 101203. https://doi.org/10.1016/j.learninstruc.2019.04.004

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data driven approaches in digital education* (pp. 82–96). Springer International Publishing. https://doi.org/10.1007/978-3-319-66610-5_7.

Johnson, T. R., Lyons, R., Kopper, R., Johnsen, K. J., Lok, B. C., & Cendan, J. C. (2014). Virtual patient simulations and optimal social learning context: A replication of an aptitude-treatment interaction effect. *Medical Teacher, 36*(6), 486–494. https://doi.org/10.3109/0142159X.2014.890702

Jossberger, H., Breckwoldt, J., & Gruber, H. (2022). Promoting expertise through simulation (PETS): A conceptual framework. *Learning and Instruction, 82*, Article 101686. https://doi.org/10.1016/j.learninstruc.2022.101686

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review, 19*(4), 509–539.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist, 38*(1), 23–31.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kelly, G. (2008). Inquiry, activity and epistemic practice. In R. A. Duschl, & R. E. Grandy (Eds.), *Teaching scientific inquiry: Recommendations for research and implementation* (pp. 99–117). Brill. https://doi.org/10.1163/9789460911453_009.

Kitto, K., Hicks, B., & Buckingham Shum, S. (2023). Using causal models to bridge the divide between big data and educational theory. *British Journal of Educational Technology, 54*(5), 1095–1124. https://doi.org/10.1111/bjet.13321

Knogler, M., Harackiewicz, J. M., Gegenfurtner, A., & Lewalter, D. (2015). How situational is situational interest? Investigating the longitudinal structure of situational interest. *Contemporary Educational Psychology, 43*, 39–50. https://doi.org/10.1016/j.cedpsych.2015.08.004

Koedinger, K. R., & Aleven, V. (2007). *Exploring the Assistance Dilemma in Experiments with Cognitive Tutors., 19*, 239–264.

Kollar, I., Fischer, F., & Hesse, F. W. (2006). Collaboration scripts – A conceptual analysis. *Educational Psychology Review, 18*, 159–185. https://doi.org/10.1007/s10648-006-9007-2

Kolodner, J. L. (1992). An introduction to case-based reasoning. *Artificial Intelligence Review, 6*(1), 3–34. https://doi.org/10.1007/BF00155578

Kolovou, D., Naumann, A., Hochweber, J., & Praetorius, A.-K. (2021). Content-specificity of teachers' judgment accuracy regarding students' academic achievement. *Teaching and Teacher Education, 100*, Article 103298. https://doi.org/10.1016/j.tate.2021.103298

Kosel, C., Holzberger, D., & Seidel, T. (2021). Identifying expert and novice visual Scanpath patterns and their relationship to assessing learning-relevant student characteristics. *Frontiers in Education, 5*. https://doi.org/10.3389/feduc.2020.612175

Kovanovic, V., Azevedo, R., Gibson, D. C., & Ifenthaler, D. (2023). Data for unobtrusive observations of learning: From trace data to multimodal data. In V. Kovanovic, R. Azevedo, D. C. Gibson, & D. lfenthaler (Eds.), *Unobtrusive observations of learning in digital environments: Examining behavior, cognition, emotion, metacognition and social processes using learning analytics* (pp. 119–121). Springer International Publishing. https://doi.org/10.1007/978-3-031-30992-2_8.

Krapp, A. (2005). Basic needs and the development of interest and intrinsic motivational orientations. *Learning and Instruction, 15*(5), 381–395. https://doi.org/10.1016/j.learninstruc.2005.07.007

Kron, S., Sommerhoff, D., Achtner, M., Stürmer, K., Wecker, C., Siebeck, M., & Ufer, S. (2022). Cognitive and motivational person characteristics as predictors of diagnostic performance: Combined effects on pre-service teachers' diagnostic task selection and accuracy. *Journal für Mathematik-Didaktik, 43*(1), 135–172. https://doi.org/10.1007/s13138-022-00200-2

Kron, S., Sommerhoff, D., Achtner, M., & Ufer, S. (2021). Selecting mathematical tasks for assessing student's understanding: Pre-service teachers' sensitivity to and adaptive use of diagnostic task potential in simulated diagnostic one-to-one interviews. *Frontiers in Education, 6*. https://doi.org/10.3389/feduc.2021.604568

Küchemann, S., Avila, K. E., Dinc, Y., Hortmann, C., Revenga, N., Ruf, V., … Kuhn, J. (2024). Are large multimodal foundation models all we need? *On Opportunities and Challenges of these Models in Education.*. https://doi.org/10.35542/osf.io/n7dvf

Küchemann, S., Klein, P., Becker, S., Kumari, N., & Küchemann, S. (2020). Classification of students' conceptual understanding in STEM education using their visual attention distributions: A comparison of three machine-learning approaches. In *Proceedings of the 12th international conference on computer supported education. 12th international conference on computer supported education, Vol. 1* (pp. 36–46). https://doi.org/10.5220/0009359400360046

Kucirkova, N., Gerard, L., & Linn, M. C. (2021). Designing personalised instruction: A research and design framework. *British Journal of Educational Technology, 52*(5), 1839–1861. https://doi.org/10.1111/bjet.13119

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.

Lee, J., & Park, O.-C. (2008). Adaptive instructional systems. In J. M. Spector, M. D. Merrill, J. Van Merriënboer, & M. P. Driscoll (Eds.), *Handbook of research on educational communications and technology* (pp. 469–484). Lawrence Erlbaum Associates.

Lehtinen, E. (2023). Can simulations help higher education in training professional skills? *Learning and Instruction, 86*, Article 101772. https://doi.org/10.1016/j.learninstruc.2023.101772

Lichtenberger, A., Wagner, C., Hofer, S. I., Stern, E., & Vaterlaus, A. (2017). Validation and structural analysis of the kinematics concept test. *Physical Review Physics Education Research, 13*(1), Article 010115. https://doi.org/10.1103/PhysRevPhysEducRes.13.010115

Lim, L., Bannert, M., van der Graaf, J., Molenaar, I., Fan, Y., Kilgour, J., … Gašević, D. (2021). Temporal assessment of self-regulated learning by mining students' think-aloud protocols. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.749749

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., … Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior, 139*(C). https://doi.org/10.1016/j.chb.2022.107547

Lipnevich, A. A., & Panadero, E. (2021). A review of feedback models and theories: Descriptions, definitions, and conclusions. *Frontiers in Education, 6*. https://doi.org/10.3389/feduc.2021.720195

Lippert, A., Shubeck, K., Morgan, B., Hampton, A., & Graesser, A. (2020). Multiple agent designs in conversational intelligent tutoring systems. *Technology, Knowledge and Learning: Learning Mathematics, Science and the Arts in the Context of Digital Technologies, 25*(3), 443–463. https://doi.org/10.1007/s10758-019-09431-8

Liu, L., Hao, J., von Davier, A. A., Kyllonen, P., & Zapata-Rivera, J.-D. (2016). A tough nut to crack: Measuring collaborative problem solving. In *Handbook of research on technology tools for real-world skill development* (pp. 344–359). IGI Global.

Lu, J., Batra, D., Parikh, D., & Lee, S. (2019). *ViLBERT: Pretraining task-agnostic Visiolinguistic representations for vision-and-language tasks (arXiv:1908.02265). arXiv*. https://doi.org/10.48550/arXiv.1908.02265

Mamede, S., & Schmidt, H. G. (2017). Reflection in medical diagnosis: A literature review. *Health Professions Education, 3*(1), 15–25. https://doi.org/10.1016/j.hpe.2017.01.003

Mamede, S., Splinter, T. A. W., Gog, T., van, Rikers, R. M. J. P., & Schmidt, H. G. (2012). Exploring the role of salient distracting clinical features in the emergence of diagnostic errors and the mechanisms through which reflection counteracts mistakes. *BMJ Quality and Safety, 21*(4), 295–300. https://doi.org/10.1136/bmjqs-2011-000518

Mangaroska, K., Sharma, K., Gašević, D., & Giannakos, M. (2022). Exploring students' cognitive and affective states during problem solving through multimodal data: Lessons learned from a programming activity. *Journal of Computer Assisted Learning, 38*(1), 40–59. https://doi.org/10.1111/jcal.12590

Martin, M., Farrell, M., Seidel, T., Rieß, W., Könings, K. D., van Merriënboer, J. J. G., & Renkl, A. (2022). Focused self-explanation prompts and segmenting foster pre-service teachers' professional vision—But only during training! *International Journal of Educational Technology in Higher Education, 19*(1), 34. https://doi.org/10.1186/s41239-022-00331-z

Martin, M., Farrell, M., Seidel, T., Rieß, W., Könings, K. D., van Merriënboer, J. J. G., & Renkl, A. (2023). Knowing what matters: Short introductory texts support pre-service teachers' professional vision of tutoring interactions. *Teaching and Teacher Education, 124*, Article 104014. https://doi.org/10.1016/j.tate.2023.104014

Mayer, R. E. (2014). Cognitive theory of multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 43–71). Cambridge University Press. https://doi.org/10.1017/CBO9781139547369.005.

Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education, 57*(4), 632–645. https://doi.org/10.1111/ejed.12527

Molenaar, I., Mooij, S., de, Azevedo, R., Bannert, M., Järvelä, S., & Gašević, D. (2023). Measuring self-regulated learning and the role of AI: Five years of research using multimodal multichannel data. *Computers in Human Behavior, 139*, Article 107540. https://doi.org/10.1016/j.chb.2022.107540

Motz, B., Quick, J., Schroeder, N., Zook, J., & Gunkel, M. (2019). The validity and utility of activity logs as a measure of student engagement. In *Proceedings of the 9th international conference on Learning Analytics & Knowledge* (pp. 300–309). https://doi.org/10.1145/3303772.3303789

Mutlu-Bayraktar, D., Cosgun, V., & Altan, T. (2019). Cognitive load in multimedia learning environments: A systematic review. *Computers & Education, 141*, Article 103618. https://doi.org/10.1016/j.compedu.2019.103618

Namoun, A., & Alshanqiti, A. (2021). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences, 11*(1). https://doi.org/10.3390/app11010237. Article 1.

Narciss, S. (2013). Designing and evaluating tutoring feedback strategies for digital learning environments on the basis of the interactive tutoring feedback model. *Digital Education Review, 0*(23), 7–26.

Narciss, S., Sosnovsky, S., Schnaubert, L., Andrès, E., Eichelmann, A., Goguadze, G., & Melis, E. (2014). Exploring feedback and student characteristics relevant for personalizing feedback strategies. *Computers & Education, 71*, 56–76. https://doi.org/10.1016/j.compedu.2013.09.011

Nickl, M., Huber, S. A., Sommerhoff, D., Codreanu, E., Ufer, S., & Seidel, T. (2022). Video-based simulations in teacher education: The role of learner characteristics as capacities for positive learning experiences and high performance. *International Journal of Educational Technology in Higher Education, 19*(1), 45. https://doi.org/10.1186/s41239-022-00351-9

Nickl, M., Sommerhoff, D., Böheim, R., Ufer, S., & Seidel, T. (2024). Fostering pre-service teachers' assessment skills in a video simulation. *Zeitschrift Für Pädagogische Psychologie, 38*(1–2), 27–34. https://doi.org/10.1024/1010-0652/a000362

Nickl, M., Sommerhoff, D., Radkowitsch, A., Huber, S. A., Bauer, E., Ufer, S., … Seidel, T. (2024). Effects of real-time adaptivity of scaffolding: Supporting pre-service mathematics teachers' assessment skills in simulations. *Learning and Instruction, 94*, Article 101994. https://doi.org/10.1016/j.learninstruc.2024.101994

Nicol, D. (2021). The power of internal feedback: Exploiting natural comparison processes. *Assessment & Evaluation in Higher Education, 46*(5), 756–778. https://doi.org/10.1080/02602938.2020.1823314

Norman, G. (2005). Research in clinical reasoning: Past history and current trends. *Medical Education, 39*(4), 418–427.

Norman, G., Dore, K., & Grierson, L. (2012). The minimal relationship between simulation fidelity and transfer of learning. *Medical Education, 46*(7), 636–647. https://doi.org/10.1111/j.1365-2923.2012.04243.x

Norman, G., Young, M., & Brooks, L. (2007). Non-analytical models of clinical reasoning: The role of experience. *Medical Education, 41*(12), 1140–1145.

Nye, B. D., Davis, D. M., Rizvi, S. Z., Carr, K., Swartout, W., Thacker, R., & Shaw, K. (2021). Feasibility and usability of MentorPal, a framework for rapid development of virtual mentors. *Journal of Research on Technology in Education, 53*(1), 21–43. https://doi.org/10.1080/15391523.2020.1771640

Olsen, J. K., Sharma, K., Rummel, N., & Aleven, V. (2020). Temporal analysis of multimodal data to predict collaborative learning outcomes. *British Journal of Educational Technology, 51*(5), 1527–1547. https://doi.org/10.1111/bjet.12982

OpenAI. (2023). *GPT-4 technical report (ArXiv, 2303)*.

Orchard, C. A., King, G. A., Khalili, H., & Bezzina, M. B. (2012). Assessment of Interprofessional team collaboration scale (AITCS): Development and testing of the instrument. *The Journal of Continuing Education in the Health Professions, 32*(1), 58–67. https://doi.org/10.1002/chp.21123

Ouyang, F., Wu, M., Zhang, L., Xu, W., Zheng, L., & Cukurova, M. (2023). Making strides towards AI-supported regulation of learning in collaborative knowledge construction. *Computers in Human Behavior, 142*, Article 107650. https://doi.org/10.1016/j.chb.2023.107650

Papa, F. J. (2016). A dual processing theory based approach to instruction and assessment of diagnostic competencies. *Medical Science Educator, 26*(4), 787–795. https://doi.org/10.1007/s40670-016-0326-8

Pea, R. D. (2004). The social and technological dimensions of scaffolding and related theoretical concepts for learning, education, and human activity. *The Journal of the Learning Sciences, 13*(3), 423–451.

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315–341. https://doi.org/10.1007/s10648-006-9029-9

Pekrun, R., & Linnenbrink-Garcia, L. (2012). Academic emotions and student engagement. In *Handbook of research on student engagement* (pp. 259–282). Boston, MA: Springer. https://doi.org/10.1007/978-1-4614-2018-7_12.

Pekrun, R., & Linnenbrink-Garcia, L. (2014). Introduction to emotions in education. In *International handbook of emotions in education*. Routledge.

Pfeiffer, J., Meyer, C. M., Schulz, C., Kiesewetter, J., Zottmann, J., Sailer, M., … Gurevych, I. (2019). *Famulus: Interactive annotation and feedback generation for teaching diagnostic reasoning (arXiv:1908.11254). arXiv*. https://doi.org/10.48550/arXiv.1908.11254

Pieger, E., & Bannert, M. (2018). Differential effects of students' self-directed metacognitive prompts. *Computers in Human Behavior, 86*, 165–173. https://doi.org/10.1016/j.chb.2018.04.022

Plass, J. L., & Pawar, S. (2020). Toward a taxonomy of adaptivity for learning. *Journal of Research on Technology in Education, 52*(3), 275–300. https://doi.org/10.1080/15391523.2020.1719943

Quintana, C., Reiser, B. J., Davis, E. A., Krajcik, J., Fretz, E., Duncan, R. G., … Soloway, E. (2004). A scaffolding design framework for software to support science inquiry. *Journal of the Learning Sciences, 13*(3), 337–386. https://doi.org/10.1207/s15327809jls1303_4

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., … Sutskever, I. (2021). Learning transferable visual models from natural language supervision. arXiv:2103.00020 *arXiv*. https://doi.org/10.48550/arXiv.2103.00020.

Radkowitsch, A., Sailer, M., Schmidmaier, R., Fischer, M. R., & Fischer, F. (2021). Learning to diagnose collaboratively – Effects of adaptive collaboration scripts in agent-based medical simulations. *Learning and Instruction, 75*, Article 101487. https://doi.org/10.1016/j.learninstruc.2021.101487

Radkowitsch, A., Sommerhoff, D., Nickl, M., Codreanu, E., Ufer, S., & Seidel, T. (2023). Exploring the diagnostic process of pre-service teachers using a simulation – A latent profile approach. *Teaching and Teacher Education, 130*, Article 104172. https://doi.org/10.1016/j.tate.2023.104172

Rahimi, S., & Shute, V. J. (2024). Stealth assessment: A theoretically grounded and psychometrically sound method to assess, support, and investigate learning in technology-rich environments. *Educational Technology Research and Development, 72*(5), 2417–2441. https://doi.org/10.1007/s11423-023-10232-1

Raković, M., Iqbal, S., Li, T., Fan, Y., Singh, S., Surendrannair, S., Kilgour, J., van der Graaf, J., Lim, L., Molenaar, I., Bannert, M., Moore, J., & Gašević, D. (2023). Harnessing the potential of trace data and linguistic analysis to predict learner performance in a multi-text writing task. *Journal of Computer Assisted Learning, 39*(3), 703–718. https://doi.org/10.1111/jcal.12769

Renkl, A. (2014). Toward an instructionally oriented theory of example-based learning. *Cognitive Science, 38*(1), 1–37. https://doi.org/10.1111/cogs.12086

Richter, M., & Slade, K. (2017). Interpretation of physiological indicators of motivation: Caveats and recommendations. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology, 119*, 4–10. https://doi.org/10.1016/j.ijpsycho.2017.04.007

Richters, C., Stadler, M., Radkowitsch, A., Schmidmaier, R., Fischer, M. R., & Fischer, F. (2023). Who is on the right track? Behavior-based prediction of diagnostic success in a collaborative diagnostic reasoning simulation. *Large-Scale Assessments in Education, 11*(1), 3. https://doi.org/10.1186/s40536-023-00151-1

Richters, C., Schmidmaier, R., Popov, V., Schredelseker, J., Fischer, F., & Fischer, M. R. (2024). Intervention skills–a neglected field of research in medical education and beyond. *GMS Journal for Medical Education, 41*(4). https://doi.org/10.3205/zma00170. Doc48.

Rong, Y., Leemann, T., Nguyen, T., Fiedler, L., Qian, P., Unhelkar, V., … Kasneci, E. (2023). *Towards human-centered explainable AI: A survey of user studies for model explanations (arXiv:2210.11584). arXiv*. https://doi.org/10.48550/arXiv.2210.11584

Roos, A.-L., Goetz, T., Voracek, M., Krannich, M., Bieg, M., Jarrell, A., & Pekrun, R. (2021). Test anxiety and physiological arousal: A systematic review and Meta-analysis. *Educational Psychology Review, 33*(2), 579–618. https://doi.org/10.1007/s10648-020-09543-z

Rosé, C. P., McLaughlin, E. A., Liu, R., & Koedinger, K. R. (2019). Explanatory learner models: Why machine learning (alone) is not the answer. *British Journal of Educational Technology, 50*(6), 2943–2958. https://doi.org/10.1111/bjet.12858

Rovers, S. F. E., Clarebout, G., Savelberg, H. H. C. M., de Bruin, A. B. H., & van Merriënboer, J. J. G. (2019). Granularity matters: Comparing different ways of measuring self-regulated learning. *Metacognition and Learning, 14*(1), 1–19. https://doi.org/10.1007/s11409-019-09188-6

Rummel, N., Spada, H., & Hauser, S. (2009). Learning to collaborate while being scripted or by observing a model. *International Journal of Computer-Supported Collaborative Learning, 4*(1), 69–92. https://doi.org/10.1007/s11412-008-9054-4

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Sadler, D. R. (1989). Formative assessment and the Design of Instructional Systems. *Instructional Science, 18*(2), 119–144.

Sailer, M., Bauer, E., Hofmann, R., Kiesewetter, J., Glas, J., Gurevych, I., & Fischer, F. (2023). Adaptive feedback from artificial neural networks facilitates pre-service teachers' diagnostic reasoning in simulation-based learning. *Learning and Instruction, 83*, Article 101620.

Sailer, M., Ninaus, M., Huber, S. E., Bauer, E., & Greiff, S. (2024). The End is the Beginning is the End: The closed-loop learning analytics framework. *Computers in Human Behavior, 158*, Article 108305. https://doi.org/10.1016/j.chb.2024.108305

Salehian Kia, F., Bernacki, M. L., & Greene, J. A. (2023). Measuring and validating assumptions about self-regulated learning with multimodal data. In V. Kovanovic, R. Azevedo, D. C. Gibson, & D. lfenthaler (Eds.), *Unobtrusive observations of learning in digital environments: Examining behavior, cognition, emotion, metacognition and social processes using learning analytics* (pp. 123–140). Springer International Publishing. https://doi.org/10.1007/978-3-031-30992-2_9.

Schiefele, U., Streblow, L., Ermgassen, U., & Moschner, B. (2003). The influence of learning motivation and learning strategies on college achievement: Results of a longitudinal analysis. *Zeitschrift Für Pädagogische Psychologie / German Journal of Educational Psychology, 17*(3–4), 185–198. https://doi.org/10.1024//1010-0652.17.34.185

Schneider, D., Slaughter, V. P., & Dux, P. E. (2017). Current evidence for automatic theory of mind processing in adults. *Cognition, 162*, 27–31. https://doi.org/10.1016/j.cognition.2017.01.018

Schneider, S., Beege, M., Nebel, S., & Rey, G. D. (2018). A meta-analysis of how signaling affects learning with media. *Educational Research Review, 23*, 1–24. https://doi.org/10.1016/j.edurev.2017.11.001

Seidel, T. (2022). Professionelle Unterrichtswahrnehmung als Teil von Expertise im Lehrberuf. Weiterentwicklungsperspektiven für die videobasierte Lehrerforschung. In M. Holodynski, N. Meschede, R. Junker, & V. Zucker (Eds.), *Lehren und Forschen mit Videos in der Lehrkräftebildung (pp. 17–36)* (Waxmann).

Seidel, T., Farrell, M., Martin, M., Rieß, W., & Renkl, A. (2022). Developing scripted video cases for teacher education: Creating evidence-based practice representations using mock ups. *Frontiers in Education, 7*. https://doi.org/10.3389/feduc.2022.965498

Seidel, T., Kosel, C., Böheim, R., Gegenfurtner, A., & Stürmer, K. (2024). A cognitive perspective on teachers' professional vision: How teachers' professional knowledge shapes a professional vision. In A. Gegenfurtner, & R. Stahnke (Eds.), *Teacher Professional Vision: Theoretical and Methodological Advances* (pp. 43–56). Routledge.

Seidel, T., Renkl, A., & Rieß, W. (2021). Basisdimensionen für Unterrichtsqualität im Fachkontext konkretisieren: Die Rolle von Unterrichtsartefakten und Bestimmung von Standardsituationen. *Unterrichtswissenschaft, 49*(2), 293–301. https://doi.org/10.1007/s42010-021-00108-9

Seidel, T., & Stürmer, K. (2014). Modeling and measuring the structure of professional vision in preservice teachers. *American Educational Research Journal, 51*(4), 739–771. https://doi.org/10.3102/0002831214531321

Seidel, T., Stürmer, K., Prenzel, M., Jahn, G., & Schäfer, S. (2017). Investigating pre-service teachers' professional vision within university-based teacher education. In D. Leutner, J. Fleischer, J. Grünkorn, & E. Klieme (Eds.), *Competence assessment in education: Research, models and instruments* (pp. 93–109). Springer International Publishing. https://doi.org/10.1007/978-3-319-50030-0_7.

Seidel, T., Stürmer, K., Schäfer, S., & Jahn, G. (2015). How preservice teachers perform in teaching events regarding generic teaching and learning components. *Zeitschrift Für Entwicklungspsychologie Und Pädagogische Psychologie, 47*(2), 84–96. https://doi.org/10.1026/0049-8637/a000125

Seufert, T. (2018). The interplay between self-regulation in learning and cognitive load. *Educational Research Review, 24*, 116–129. https://doi.org/10.1016/j.edurev.2018.03.004

Shulman, L. S. (1987). Knowledge and teaching: Foundations of the new reform. *Harvard Educational Review, 57*(1), 1–23.

Shulman, L. S. (1998). Theory, practice, and the education of professionals. *The Elementary School Journal, 98*(5), 511–526.

Sommerhoff, D., Codreanu, E., Nickl, M., Ufer, S., & Seidel, T. (2023). Pre-service teachers' learning of diagnostic skills in a video-based simulation: Effects of conceptual vs. interconnecting prompts on judgment accuracy and the diagnostic process. *Learning and Instruction, 83*, Article 101689. https://doi.org/10.1016/j.learninstruc.2022.101689

Stadler, M., Fischer, F., & Greiff, S. (2019). Taking a closer look: An exploratory analysis of successful and unsuccessful strategy use in complex problems. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.00777

Stadler, M., Niepel, C., & Greiff, S. (2019). Differentiating between static and complex problems: A theoretical framework and its empirical validation. *Intelligence, 72*, 1–12.

Stadler, M., Sailer, M., & Fischer, F. (2021). Knowledge as a formative construct: A good alpha is not always better. *New Ideas in Psychology, 60*, Article 100832. https://doi.org/10.1016/j.newideapsych.2020.100832

Stark, R., Kopp, V., & Fischer, M. R. (2011). Case-based learning with worked examples in complex domains: Two experimental studies in undergraduate medical education. *Learning and Instruction, 21*(1), 22–33. https://doi.org/10.1016/j.learninstruc.2009.10.001

Steinert, S., Avila, K. E., Ruzika, S., Kuhn, J., & Küchemann, S. (2024). Harnessing large language models to develop research-based learning assistants for formative feedback. *Smart Learning Environments, 11*(1), 62. https://doi.org/10.1186/s40561-024-00354-1

Stern, E. (2017). Individual differences in the learning potential of human beings. *npj Science of Learning, 2*(1), 2. https://doi.org/10.1038/s41539-016-0003-0

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Tabak, I., & Kyza, E. A. (2018). *Research on scaffolding in the learning sciences: A methodological perspective*. In International Handbook of the Learning Sciences: Routledge.

Taub, M., Azevedo, R., Rajendran, R., Cloude, E. B., Biswas, G., & Price, M. J. (2021). How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system? *Learning and Instruction, 72*, Article 101200. https://doi.org/10.1016/j.learninstruc.2019.04.001

Tay, Y., Dehghani, M., Bahri, D., & Metzler, D. (2022). *Efficient transformers: A survey (arXiv:2009.06732). arXiv*. https://doi.org/10.48550/arXiv.2009.06732

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. *Educational Psychology Review, 33*(3), 863–882. https://doi.org/10.1007/s10648-020-09570-w

Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., … Lample, G. (2023). LLaMA: Open and efficient foundation language models. *(arXiv: 2302.13971). arXiv*. https://doi.org/10.48550/arXiv.2302.13971

Tulis, M., Steuer, G., & Dresel, M. (2018). Positive beliefs about errors as an important element of adaptive individual dealing with errors during academic learning. *Educational Psychology, 38*(2), 139–158. https://doi.org/10.1080/01443410.2017.1384536

Urhahne, D., & Wijnia, L. (2021). A review on the accuracy of teacher judgments. *Educational Research Review, 32*, Article 100374. https://doi.org/10.1016/j.edurev.2020.100374

van der Graaf, J., Lim, L., Fan, Y., Kilgour, J., Moore, J., Gašević, D., … Molenaar, I. (2022). The dynamics between self-regulated learning and learning outcomes: An exploratory approach and implications. *Metacognition and Learning, 17*(3), 745–771. https://doi.org/10.1007/s11409-022-09308-9

van der Graaf, J., Raković, M., Fan, Y., Lim, L., Singh, S., Bannert, M., Gašević, D., & Molenaar, I. (2023). How to design and evaluate personalized scaffolds for self-regulated learning. *Metacognition and Learning, 18*(3), 783–810. https://doi.org/10.1007/s11409-023-09361-y

van Gog, T., & Rummel, N. (2010). Example-based learning: Integrating cognitive and social-cognitive research perspectives. *Educational Psychology Review, 22*(2), 155–174. https://doi.org/10.1007/s10648-010-9134-7

van Merriënboer, J. J. G., & van, & Kirschner, P. A.. (2017). *Ten steps to complex learning: A systematic approach to four-component instructional design*. Routledge.

van Otterlo, M., & Wiering, M. (2012). Reinforcement learning and Markov decision processes. In M. Wiering, & M. van Otterlo (Eds.), *Reinforcement learning: State-of-the-art* (pp. 3–42). Springer. https://doi.org/10.1007/978-3-642-27645-3_1.

Vandewaetere, M., & Clarebout, G. (2014). Advanced Technologies for Personalized Learning, instruction, and performance. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 425–437). Springer. https://doi.org/10.1007/978-1-4614-3185-5_34.

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., … Van den Noortgate, W. (2021). Towards measuring cognitive load through multimodal physiological data. *Cognition, Technology & Work, 23*(3), 567–585. https://doi.org/10.1007/s10111-020-00641-0

Vogel, F., Wecker, C., Kollar, I., & Fischer, F. (2017). Socio-cognitive scaffolding with computer-supported collaboration scripts: A meta-analysis. *Educational Psychology Review, 29*(3), 477–511. https://doi.org/10.1007/s10648-016-9361-7

Vogel, F., & Weinberger, A. (2018). *Quantifying qualities of collaborative learning processes*. In International Handbook of the Learning Sciences: Routledge.

Vygotsky, L. S. (1980). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Walkington, C., & Bernacki, M. L. (2018). Personalization of instruction: Design dimensions and implications for cognition. *The Journal of Experimental Education, 86*(1), 50–68. https://doi.org/10.1080/00220973.2017.1380590

Walkington, C., & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. *Journal of Research on Technology in Education, 52*(3), 235–252. https://doi.org/10.1080/15391523.2020.1747757

Weinberger, A., Stegmann, K., & Fischer, F. (2007). Knowledge convergence in collaborative learning: Concepts and assessment. *Learning and Instruction, 17*(4), 416–426.

Wiedbusch, M. D., Kite, V., Yang, X., Park, S., Chi, M., Taub, M., & Azevedo, R. (2021). A theoretical and evidence-based conceptual design of MetaDash: An intelligent teacher dashboard to support teachers' decision making and students' self-regulated learning. *Frontiers in Education, 6*. https://doi.org/10.3389/feduc.2021.570229

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The power of feedback revisited: A Meta-analysis of educational feedback research. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.03087

Wood, D. (2003). Problem based learning. *BMJ, 326*(7384), 328–330. https://doi.org/10.1136/bmj.326.7384.328

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry, 17*(2), 89–100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x

Yang, F., & Stefaniak, J. (2023). A systematic review of studies exploring help-seeking strategies in online learning environments. *Online Learning, 27*(1), 107–126.

Zhang, Q., & Fiorella, L. (2023). An integrated model of learning from errors. *Educational Psychologist, 58*(1), 18–34. https://doi.org/10.1080/00461520.2022.2149525

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*(3), 329–339. https://doi.org/10.1037/0022-0663.81.3.329

Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulation: Where metacognition and motivation intersect. In *Handbook of metacognition in education* (pp. 299–315). Routledge/Taylor & Francis Group.

Zimmerman, B. J., & Schunk, D. H. (2011). *Self-regulated learning and performance: An introduction and an overview*. In Handbook of Self-Regulation of Learning and Performance: Routledge.