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Review

Personalization through adaptivity or adaptability? A meta-analysis on simulation-based learning in higher education

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A B S T R A C T

This meta-analysis builds on 217 empirical studies in higher education and investigates the role of the different forms of adaptivity and adaptability as personalization strategies in simulation-based learning environments for complex skills in higher education. The strategies used to personalize scaffolding and task progression were the central point in this meta-analysis. We identified conditions under which personalization advances complex skills in higher education. The results indicate that whereas adaptivity (i.e., computer makes decisions) is more effective for scaffolding, adaptability (the decisions made by individual learners) seem more beneficial for task progression. We conclude that adaptivity and adaptability can be effectively used to personalize simulation-based learning environments in higher education to better address needs of learners with different learning needs. We also discuss the potential of artificial intelligence for empowering personalization in simulation-based learning.

1. Problem statement

Simulation-based learning is regarded as a promising means to support learners in acquiring a range of complex skills in different domains of higher education. This is empirically backed up by multiple systematic reviews and meta-analyses highlighting that simulations positively affect learning outcomes (e.g., Chernikova et al., 2020; Cook et al., 2013; Hegland et al., 2017; Theelen et al., 2019). However, empirical research also highlights that (i) simulations – as many other types of learning environments – do not show uniform effects for all learners and (ii) that learning effects can be further increased by additional instructional support (Chernikova et al., 2020; Belland et al., 2017). Combining both aspects leads to the idea of personalization of learning in simulation-based learning environments, which can be achieved through (i) adaptive (i.e., system-adjusted) and (ii) adaptable (i.e., human-adjusted) learning environments and instructional support (e.g., scaffolding), respectively. Furthermore, exploring adaptivity of learning environments is particularly interesting against the background of artificial intelligence (AI), as AI offers a range of new possibilities for fine-tuned adaptivity and adaptability (e.g., Holstein et al., 2020).

Even though its benefits are expected theoretically (e.g., Aleven et al., 2016; Plass & Pawar, 2020), only little and rather unsystematic evidence exists for the effects of embedding adaptivity and adaptability in simulation-based learning environments for various purposes in higher education, including but not limited to learning complex skills. Therefore, we apply a meta-analytical approach to

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shed light on the effectiveness of the different forms of adaptivity and adaptability in simulation-based learning environments for complex skills in higher education. We aim to systematize existing evidence, advance theory, and offer insights and recommendations for the effective design of simulations.

2. Theoretical background

2.1. Simulation-based learning and instructional support

Simulations are being used as effective educational tools in higher education (e.g., Chernikova et al., 2020; Cook et al., 2013), as they offer the opportunity for learners to interact with representations of professional practice, decomposed into components that learners can interact with (Grossman et al., 2009). These components can enable students to focus on relevant aspects of that practice without being overwhelmed (e.g., Codreanu et al., 2020). These so-called "approximations-of-practices" give learners the opportunity to engage in more or less comprehensive and authentic professional practices (Grossman et al., 2009). Simulations come in various form and range from document-based simulations (e.g. with written vignettes), to non-digital types of simulations such as role-plays or clinical simulations with professional actors to more digital types of simulations such as video-based or VR-based simulations or surgery simulations using a bio-mechanical simulator (e.g., Gao et al., 2021; Huang et al., 2023; Kron et al., 2021). However, the most important elements of a simulation are that (1) a relevant aspect of reality is represented (see approximation of practice by Grossman et al. (2009), (2) learners have the opportunity to interact with the representations of practice, and (3) that the development of the simulated situation is influenced by learners' activities or decisions (Heitzmann et al., 2019).

Even though simulations can be highly effective learning environments (e.g., Chernikova et al., 2020, Cook et al., 2013), the underlying design principles that make them so effective for learning are not yet fully understood (Bauer et al., 2023). One aspect that is particularly relevant for simulations as learning environments is that learning with simulations can be further improved through different forms of instructional support (e.g., scaffolding) particularly when such support is tailored to the individual learners' characteristics and needs (e.g., Chernikova et al., 2020). Scaffolding can be used in different types of learning environments and is conceptualized as a temporary shift of control from the learner to a more knowledgeable agent (Tabak & Kyza, 2018), directed at the learning processes and having the purpose of enabling learners to solve problems that they could not solve without that support (e.g., Quintana et al., 2004). It is important to note that scaffolding is often expected to work in the zone of proximal development (e.g., Vygotsky, 1978) and can only support the learner with the tasks matching or slightly going beyond their current competence level.

Compared to typical real-life practice in many domains, simulations have the clear advantage that they can efficiently provide scaffolding that can be more flexibly adjusted to the current level of a learner's prerequisites. Learners can make use of the potential to work, repeatedly, with authentic cases without being cognitively overwhelmed.

This meta-analysis focuses on the personalization of scaffolding, as one of the means of instructional support. Scaffolding directed at the learning process is usually additional information that learners receive intending to direct their activities in a learning environment in a way that is beneficial for the learning processes (e.g., procedural facilitation, Bereiter & Scardamalia, 1993) and the learning outcomes. It can involve different forms of prompts that can be directed at cognitive, metacognitive, affective-motivational, or social processes.

Taking learners' prerequisites into account through implementing representational scaffolding (Fischer et al., 2022) means that the practices in the simulation are purposefully selected from professional practices (e.g., based on informational complexity or typicality) and adjusted before or during the simulation so that they fit a learner's current level of learning prerequisites.

Within the simulated scenario, there might also be an opportunity to select particular tasks (e.g., opportunity to start with easy task or particular activity and proceed to more complex ones). This opportunity is also connected to the idea of task progression, introduced by Plass and Pawar (2020) or navigation and is in focus in this meta-analysis. To address the task progression, we consider if the order of tasks is fixed or can be changed by the learner or the system. According to the results of a recent meta-analysis on simulation-based learning in higher education (Chernikova et al., 2020), the design of representations of practice for simulations using representational scaffolding might offer potential for improving learning. However, the authors also report a fair amount of heterogeneity of the effect sizes within each group of instructional support measures. We assume that one possible further variable contributing to this heterogeneity is whether the amount and exact time of instructional support is determined by the learning environment (e.g., instructor or pre-programmed system) or by the individual learner (or a mix). This decision on the need for instructional support seems to be crucial for simulation-based learning as it provides an opportunity to personalize learning based on learners' needs and prerequisites (e.g., prior knowledge).

2.2. Prior knowledge and personalization

Developing and advancing complex skills and competences in higher education relies on professional knowledge as both a learning prerequisite and a building block of the skill (Blömeke et al., 2015). Prior knowledge is thus generally considered one of the most important learners' prerequisites, and prior research in diverse areas has underlined its importance for performance and learning performance (Schneider & Preckel, 2017, Simonsmeier et al., 2022). Prior knowledge can be operationalized as familiarity (conceptual and procedural) either with the content or the context of a learning environment (see Chernikova et al., 2020). As a learning prerequisite, knowledge is also relevant for personalizing a learning environment.

Personalization from an educational perspective refers to tailoring instruction to the needs of an individual to increase its effectiveness (Kucirkova et al., 2021). Personalization can thus be defined as "the data-based adjustment of any aspect of instructional practice to relevant characteristics of a specific learner" (Tetzlaff et al., 2021, p. 865). Kucirkova and colleagues (2021) outline different forms of personalization. The initial form, referred to as adaptive personalization, involves a system making choices driven by data patterns. In the second form, known as adaptable personalization, individuals make choices based on their own preferences, interests, or comprehension. A system supports an individual's choices, for example, by presenting options but letting the learners decide which option to take. In this meta-analysis, we link this framework with a framework on adaptivity, suggested by Plass and Pawar (2020) to develop scenarios of adaptive and adaptable learning environments.

2.3. Adaptivity and adaptability in simulations

Adaptivity. As per a widely recognized categorization, a modification made by a computer is referred to as adaptivity (Fischer, 2001). Adaptivity denotes a computer-assisted learning system's capacity to identify various learner characteristics and tailor the learning environment to cater to an individual learner's particular requirements (e.g., through additional instructional support), all intending to improve learning outcomes (Plass and Pawar, 2020b). Adaptivity, thus focuses on the opportunity to alter the amount, type, or timing of instructional support or the task progression (e.g., complexity, speed or order of tasks) within a learning environment to address the needs of each individual learner optimally. This operationalization of adaptive instructional support relies on the framework suggested by Plass and Pawar (2020). The authors point out that there might be multiple strategies to adapt a learning environment and instructional support based on different learners' characteristics, measured before or during the intervention (e.g., prior knowledge or performance). The adaptivity framework by Plass and Pawar (2020) emphasizes the customization of learning environments based on individual learner variables, including cognitive, emotional, motivational, and social factors. It involves measuring these variables and adjusting instructional support, task progression, and learning content accordingly. According to this framework (Plass & Pawar, 2020), adaptivity operates on both macro (course level) and micro (activity level) scales.

Although empirical research has provided first insights into the effects of adapting some instructional support in simulations (Chernikova et al., 2020; Belland et al., 2017; Kramer et al., 2021; Nickl et al., 2024), the effectiveness of different strategies and scenarios of adaptive scaffolding is currently unclear. In educational research, adapting instructional support to the needs of a learner has a long tradition. Earlier attempts known as Aptitude Treatment interaction (ATI) did not consistently demonstrate clear effects of learning prerequisites and instructional adaptivity on learning outcomes (Snow, 1991). Nonetheless, Tetzlaff and colleagues (2021) assume methodological issues as causes for the lack of clear effects. They argue that in previous ATI research, subgroups of learners were often built based on their pretests and learners stayed in those groups statically more or less independent of how their skills developed (Tetzlaff et al., 2021). Clearer effects were achieved with intelligent tutoring systems (ITS) in which dynamic adaptations occur during learning based on the current performance of the learner (e.g., Koedinger et al., 2013). Furthermore, two recent meta-analyses highlight that some forms of instructional support (e.g., reflection phases) in problem-solving scenarios in simulation-based learning are rather beneficial for more advanced learners than for less advanced learners (Chernikova et al., 2020).

Effectively incorporating adaptivity into simulations can benefit from the advancement of AI-driven technologies, especially the emergence of generative AI techniques, which provide extensive prospects for tailoring learning environments and innovative content creation approaches. Recently, transformer-based models, like those introduced by Vaswani et al. (2017), have enabled the creation of large language models capable of almost human-like text responses. Alongside massive language models such as ChatGPT, smaller open-access alternatives exist, delivering high-quality results and allowing for fine-tuning for specific purposes. Additionally, large language models can serve as intermediaries for communication between various AI models, facilitating complex task solving and more efficient data processing, as demonstrated by Shen et al. (2023). Besides the commonly used "chatbot" option, they may overtake specific functions during the learning process that can be assigned in an advanced programming interface such as personalized feedback provision or scaffolding support. However, there are mixed results concerning generating better outcomes (Robrecht et al., 2023).

To realize adaptivity, the simulation (as a system) might benefit from an accurate learner model. Therefore, a certain amount of data collection and interpretation is necessary (e.g., Debeer et al., 2021; Plass & Pawar, 2020). Advancements in the design of learner models (e.g., Brusilovsky & Millán, 2007; Shute & Zapata-Rivera, 2012), as well as in technologies such as natural language processing and other AI make a correct interpretation of complex user data more likely. However, even accuracy rates of 80–90% imply that the learner models generated by the simulation may lead to sub-optimal personalization of subsequent instruction. It also seems plausible that a simulation can diagnose certain types of learners' behavior (e.g., errors) better than others or that a simulation can offer adequate personalized support only for some learners, but not for others (e.g., for learners with low/high prior knowledge). Because relevant mechanisms are not yet completely understood and even simulations involving recent AI can create inappropriate learner models, a broad heterogeneity of effects seems plausible.

Adaptability. The second type of personalization, adaptability (as defined by Fischer, 2001), pertains to systems that human actors, including the learners themselves, can adjust. A learning environment can thus be considered adaptable when learners have control over the instructional support or contents of the learning environment (e.g., the order of tasks) (Fischer, 2001). In other words, the learning environment can be adjusted by and to learners' needs through offering specific controls to the learner (e.g., a "hint" button). The expected effectiveness of adaptable instructional support is based on theories such as self-regulated learning (SRL) and empirical findings indicating that giving learners control over their learning is beneficial for learning outcomes (e.g., Wang et al., 2017). However, it is unclear if and to what extent the adaptability of learning environments can enhance the effects of simulation-based learning and if it is equally beneficial for learners with different levels of prior knowledge, as these may or may not be able to adapt the learning environment to their needs appropriately.

To theoretically capture underlying causal mechanisms of how and why the degree of control by the learner and thus the adaptability of a learning environment may affect learning, self-regulated learning (SRL) and self-determination theory (SDT) can be used as two important cognitive and affective-motivational theories from educational psychology.

Self-regulated learning theory (SRL) and self-determination theory (SDT) see learners as active agents who play a central role in their learning and thus emphasize their engagement in the learning process (Ryan & Deci, 2000; Zimmerman & Moylan, 2009). This includes, for example, metacognitive strategies that allow setting individual learning goals, choose appropriate strategies to achieve these goals, and to monitor their learning process and outcomes (Panadero, 2017). Metacognitive strategies also include assessing need for support and identifying possible sources to seek help from (Yang & Stefaniak, 2023). At the same time, SDT (Ryan & Deci, 2000) assumes that individuals are more intrinsically motivated to engage in certain activities, when they address their needs for autonomy, relatedness, and competence. We believe that simulation-based learning environments can create space for such engaging activities and motivate learners (e.g., Moll-Khosrawi et al., 2021). As adaptability targets exactly the learners' autonomy, by providing choices (e.g., seeking for help; choosing task to perform) and allows learners to feel in control, positive effects of adaptability can be expected (Vogel et al., 2022).

Albeit SRL and SDT imply positive effects of adaptability, theories such as cognitive load theory (Sweller, 2010) can be used to arrive at a different hypothesis: having the opportunity to adapt a learning environment may lead to an increased extraneous cognitive load and thus reduce the cognitive resources available for learning. Adaptability may thus also lead to negative effects, in particular for those learners with little available cognitive resources, for example those that experience the simulation as difficult based on a lack of prior knowledge. To sum up, learners' self-regulation skills are necessary to correctly monitor and judge their learning, understanding or competency, which allows them to correctly act on that information by selecting good strategies to deal with the task. On the other hand, self-regulation can be regarded as a complex skill itself (Wang et al., 2017) and can be targeted within simulation-based learning.

Empirical research, on the one hand, supports the idea that adaptable learning environments are beneficial for learning (e.g., Dignath & Büttner, 2008), as these can enhance the use of self-regulation skills (e.g., Wang et al., 2017), increase feelings of autonomy, support motivation (Rowe et al., 2011; Ryan et al., 2006; Snow et al., 2015), enhance effort and cognitive outcomes (Chen et al., 2019; Mercier et al., 2020). On the other hand, while learning in settings with advanced learning technologies, learners might not regulate their behavior effectively even though their learning process is not optimal (e.g., Azevedo & Feyzi-Behnagh, 2011; Kirschner, & van Merriënboer, 2013) as they might rely on the technology too much.

Given the theoretical rationale for why adaptivity and adaptability may be crucial for learning behavior in general and simulation-based learning in particular, the question arises, whether different ways to embed those in the design of a simulation can be delineated. Although both adaptivity and adaptability serve personalization and target learners' needs, there is an essential difference in the decision-making authority for the adjustments. In case of adaptivity, the decisions are made by educators/educational designers, who created algorithms to identify learners' needs (using performance measures or prior knowledge and other prerequisites as indicators) and address them in actions executed by the system (i.e., pop-up prompt in the learning environment). In contrast, in the case of adaptability, the decisions within the simulations can be made by users (in our case learners). The learners assess their own needs, based on knowledge, prior experience, or given instructions (or even prompts provided by the system), and set a request to the system for additional instructional support or an altered order of tasks, using some in-built control features of the learning environment. In both cases, the learning environment changes to a certain extent and support is given by the system. The latter might either be restricted to the pre-programmed options (i.e., specific prompts included by the designers of the system) or be more flexible in case of using generative AI (i.e., individually generated feedback).

This meta-analysis specifically focuses on adaptivity and adaptability of scaffolding and task order (e.g., navigation), which in terms of design principles can be embedded and even combined in simulation-based learning environment (e.g., Kucirkova et al., 2021). This leads to three possibilities.

First, personalization can target scaffolding in form of examples or prompts, provided to guide the learner through their processing of the simulated scenarios within a learning environment. This can be done, for example by providing learners with control over the scaffolding they receive within the learning environment or by programming the learning environment to react with a specific type or amount of scaffolding to specific indicators (e.g., prior knowledge, errors in the process, poor performance, good and fast performance).

Second, personalization can target navigation through simulation by addressing task progression within a learning environment. This can be done by providing learners with control over task progression (i.e., the order of tasks within the simulation) or by programming the learning environment to alter the task progression (e.g., provide simpler task) based on some indicators (e.g., learner error).

Third, simulation can have a default scaffolding/progression scenario, same for all learners; in this case no personalization takes place.

3. Research questions

As pointed out, there are multiple theoretical reasons to believe that adaptivity and adaptability can positively affect the effectiveness of learning environments. However, as prior empirical research so far insufficiently considers adaptivity and adaptability and effects of different types of adaptivity and adaptability are mostly unclear, we address the following research questions in this meta-analysis.

1. What scenarios are commonly used in primary studies of simulation-based learning environments in higher education to personalize learners' experience through adaptivity and adaptability? (Preliminary review question)

Focusing on personalizing the scaffolding included in a learning environment, four different basic scenarios are conceivable: (i) adaptability regarding the amount, timing, and type of scaffolding (ii) adaptivity regarding the amount, timing, and type of scaffolding with individual support for all learners, and (iii) a mix of adaptability and adaptivity with only a certain amount of responsibility by the learner and additional support by the system) (iv) neither adaptable nor adaptive (not personalized scaffolding).

Similarly, but independent of these scenarios, the focus on personalization of task progression leads to further scenarios: (i) adaptability regarding the order of (at least some of) the tasks within the learning environment vs. (ii) adaptivity with individual order of at least some of the tasks; (iii) mix of adaptability and adaptivity in selecting tasks, or (iv) default order of tasks (not personalized progression).

To examine the effects of these scenarios more closely, we address the following meta-analytical research question.

2. To what extent do these scenarios of personalizing scaffolding and task progression contribute to the effectiveness of simulation-based learning on learning outcomes?

First, we expect generally positive effects of adaptivity on learning outcomes, as learners' should receive a personalized learning experience. Moreover, based on concepts of self-regulated learning and self-determination theory as underlying learning and motivational theories, we expect that adaptability (and thus increased demands onto the learners' self-regulation) would generally lead to a higher effectiveness of simulation-based learning compared to non-adaptable environments. Finally, effects of combinations of adaptivity and adaptability with respect to task progression and scaffolding have not yet been systematically investigated, so that no hypothesis is possible.

Besides the expected generally positive effect of personalization, embedding adaptability might also increase complexity and the cognitive load posed on the learners, so that differential effects based on prior knowledge may occur. Similarly, adaptivity may be more or less beneficial for learners with different prior knowledge. We therefore address the following research question in this meta-analysis.

3. To what extent does prior knowledge moderate the effects of the personalization scenarios on learning outcomes in simulation-based learning?

Based on prior research on simulation-based learning and the very notion of adaptivity and adaptability, we assume that adaptability scenarios would be more beneficial for learners with higher prior knowledge, as they will be able to determine the suitable amount of scaffolding and/or best task order, respectively. Learners with low prior knowledge might be overwhelmed with decisions to be made, i.e. by the cognitive load produced by these, and not benefit as much. In contrast, effects of adaptive scenarios should not be dependent on prior knowledge, at least not based on cognitive load theory. Therefore, adaptive scenarios can be assumed to be more effective than adaptable scenarios for learners with low prior knowledge. The same possibly occurs for learners with higher prior knowledge, as their cognitive resources might be consumed by processing scaffolds that are redundant to the prior knowledge.

4. Method

4.1. Literature search and eligibility criteria

To address the research questions, we aimed at studies that investigate effects of simulation-based learning environments on learning outcomes (e.g., complex skills). Therewith, we replicated and updated the meta-analysis by Chernikova et al. (2020), by performing the search for studies that appeared before December 20, 2020. Keywords searched were: (simulat* OR role-play) AND (competenc* OR skill*) AND (teach* OR medic* OR higher education); databases included in search were PsycINFO, PsycARTICLES, ERIC, and MEDLINE.

To be included into this meta-analysis, studies had to focus on complex skills in higher education, such as diagnosing, decision-making, problem solving, or planning. Studies that solely focused on manual/motor skills were excluded from the analysis, as these skills are more specific and can hardly be generalized across different domains of higher education. Only studies, which used simulations to facilitate knowledge, skills, or competencies, and reporting objective measures of learning outcomes, were included. Studies which reported using simulation only for assessment purposes and studies only reporting subjective measures of learning outcomes were excluded from this analysis. Studies also had to report a "no simulation" control condition (pre-test or control group) and relevant statistical values to be included. Eligible studies were not limited to any specific study site, the origin of studies and language of conduction were not restricted. To ensure that the concepts and definitions of the core elements coded for the meta-analysis were comparable and relevant, only studies published in English were included in the analysis.

The title-abstract screening was performed in a semi-automated mode, using machine learning algorithms (Chernikova et al., 2024). These algorithms were trained (on the manually classified abstracts), validated, and tested on the data from a previous meta-analysis (Chernikova et al., 2020) to support and speed up the abstract screening process. Validation and testing have shown that the algorithms were at least as effective as experienced human raters and some of them (support vector machine and random forest) performed better than human raters in terms of accuracy (Chernikova et al., 2024). The abstracts, which were identified as eligible by at least one of two selected algorithms, were included in full-text screening. Further steps (full-text screening for eligibility and moderator coding) were performed manually by first author and research assistants.

4.2. Coding procedure

Quality of coding was reached through multiple iterations including coder training ($N = 6$) and estimation of agreement. Within the coder training, 50% of the primary studies were double coded (with a Cohen's Kappa >0.85). All discrepancies were discussed to reach the final agreement of 100%, and after agreement was reached, all the studies (including training material) were coded by one of the authors and the same student research assistants independently. The studies that did not provide enough information for an unambiguous decision were excluded from respective parts of the analysis. To address the current research questions, the following features were coded:

Adaptivity and adaptability of scaffolding was coded as: (i) adaptable scaffolding, if learners could decide over the amount, timing, or content of their scaffolding (e.g., using hint buttons in the learning environment); (ii) adaptive scaffolding, if learners received automated scaffolding based on their performance (e.g., through programmed algorithms within the learning environment); (iii) a mix of adaptive and adaptable scaffolding with only a certain amount of responsibility by the learner and additional support by the system (e.g., system offers a prompt and learners decides if they want to accept or skip it); and (iv) not personalized (i.e., non-adaptive/non-adaptable) scaffolding if any kind of static scaffolding was provided to all learners in the learning environment.

Adaptivity and adaptability of task progression was coded as: (i) adaptable task progression, if the learners had control over at least some of the tasks within the learning environment; (ii) adaptive task progression if the tasks were presented in specific order by the learning environment, depending on learners performance on the previous task; (iii) mix of adaptivity and adaptability in selecting tasks in case the system offered particular task and the learner could accept or decline the offer made by the system; and (iv) not personalized (i.e., non-adaptive/non-adaptable) task progression if tasks were presented in fixed order by the learning environment in the same way for all the participants.

Prior knowledge (familiarity of context) was coded based on the primary studies' authors statements about their learners "prior" to entering intervention/learning environment (authors mention that topic or context was unfamiliar to students vs. familiar). A demo or a lecture is instructional support provided "during" the learning and does not influence the coding of prior knowledge. Thus we could distinguish between prior knowledge that learners were coming with to the experiment, and additional knowledge that they were able to access just before and during learning. The moderator was coded as high if authors of the studies mentioned that learners had been trained in a familiar context (e.g., new relevant concepts, procedures, or performed similar tasks before), low if learners had not been trained in similar contexts (e.g., new situations or tasks in the simulation, which learners never encountered before), or mixed if some learners in the group were familiar with the context and some not (e.g., if students and professionals participated in the simulation).

Additionally, the following *control variables* were coded: type and year of publication, domain and study design (experimental, quasi-experimental, or one-group pre-post design). Type of control was coded as "baseline" if the effect of simulation was controlled by pre-test only; "pure" if control condition had no instruction (e.g., waiting control) or "instructed", if the control condition received other types of instructional support on the same topic, but no simulation.

4.3. Statistical analysis

A random-effects model and Hedges g effect size estimate were applied (Schmidt & Hunter, 2014) with the correction for correlated samples (Tanner-Smith et al., 2016). We have selected Hedges' g effect size estimate as it includes a correction factor for small sample

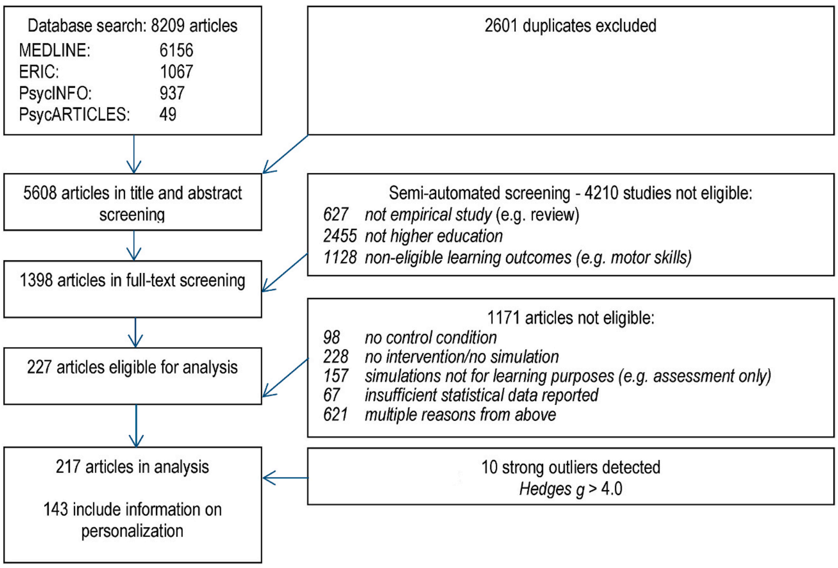

Fig. 1. PRISMA Flow Chart for the process of study selection.

sizes, which makes it a less biased estimator of the population effect size compared to Cohens ' d (Borenstein et al., 2009).

Whenever available, means and standard deviations were used to calculate the effect sizes, if authors of primary studies reported different statistics (e.g., *SE* in place of *SD*; results of statistical tests, instead of *M* and *SD* values) transformations were made based on Borenstein et al. (2009) recommendations. Procedures to trace and correct for publication bias (funnel-plot based and *p*-curve based) were performed as part of the preliminary analysis (Carter et al., 2017).

5. Results

5.1. Results of literature search and preliminary review question (RQ1)

The literature search yielded 217 eligible studies (reporting 427 comparisons) for the analysis (Fig. 1). With regard to the first research question, the review of eligible studies indicated that simulations with equal support for all learners (non-adaptive/non-adaptable scaffolding) were the most commonly used instructional setting ($N = 100$). Adaptive scaffolding was identified in $N = 25$ studies and adaptable scaffolding in $N = 12$. A combination of adaptive and adaptable scaffolding was reported in $N = 6$ studies. Relatively many primary studies did not provide sufficient information to identify the used strategies ($N = 74$) and were excluded from subsequent analyses. The coding of adaptive and adaptable task progression yielded similar results: most of the primary studies in this analysis reported fixed (non-adaptive/non-adaptable) task progression ($N = 109$); adaptable task progression was reported in ($N = 53$) studies. Adaptive task progression was not identified in the current set of studies. Other studies did not provide sufficient information for the coding.

Most of the studies were from domain of medical education (ca. 85%), followed by other domains like counseling, business, or engineering (8%); teacher education (5%) and nursing (2%). The range of analyses skills varied from technical performance (35%); general problem-solving skills (20%), managing critical situations (classroom or emergency management, 17%); diagnostic skills in teacher or medical education (10%); communication skills (11%); teamwork (2%) and other skills (5%). Control variables (domain, type of study, and type of control) did not uncover statistically significant differences between different levels of moderators and were not able to explain statistically significant amount of heterogeneity; results were in line with previous meta-analysis (Chernikova et al., 2020).

In terms of prior knowledge, most studies reported using simulations in familiar context (47%); followed by using simulations to introduce new topics or tasks (40%). Results for mixed groups of learners were reported in 13% of studies. Further detailed information about studies in the analysis can be found in OSF repository: https://osf.io/xc427/?view_only=c4d7229def8d4ed9acc94416646a5e5a.

5.2. Effects of adaptive and adaptable scenarios in simulations

To address the second research question, we performed the actual meta-analysis with $N = 143$ studies, which provided enough information to be assigned to one of the categories. The direct effects of each strategy regarding scaffolding or task progression are represented in Table 1. While the differences in the effect sizes between strategies did not reach statistical significance ($p > .05$), descriptive values indicate that adaptable scaffolding seems to be in general slightly less beneficial than adaptive scaffolding, but adaptable task progression increases effects of simulation for learners.

Looking more specifically at interactions between different strategies for scaffolding and task progression, data implies that fully adaptable learning environments ($g = 0.71$, $SE = 0.20$; $N = 7$) are significantly less beneficial ($p < .05$) than other combinations but also than non-personalized learning environments ($g = 0.85$, $SE = 0.09$; $N = 82$); differences between other moderator levels and groups are not statistically significant (see Table 2).

5.3. Role of prior knowledge

Regarding research question three on the role of prior knowledge, the effects of the different strategies for learners with high and

Table 1
Direct effect sizes for adaptive and adaptable scenarios.

Scaffolding	
Not personalized	$g = 0.92$[a] (0.08) $N = 100$
Adaptive	$g = 0.98$[a] (0.20) $N = 25$
Adaptable	$g = 0.75$[a] (0.15) $N = 12$
Adaptive and adaptable	$g = 1.10$ ns (0.55) $N = 6$
Task progression	
Not personalized	$g = 0.87$[a] (0.08) $N = 109$
Adaptable	$g = 1.10$[a] (0.14) $N = 34$
Adaptive	NA $N = 0$
Mixed	NA $N = 0$

Note: The difference between effect sizes is not statistically significant for $p > .05$ (ns).
[a] significant for $p < .05$.

Table 2
Interaction of Adaptive and Adaptable scenarios.

Scaffolding	Task progression	
	Not personalized	Adaptable
Not personalized	$g = 0.85$ (0.09); $N = 82$	$g = 1.28$ (0.18); $N = 18$
Adaptive	$g = 0.94$ (0.23); $N = 17$	$g = 1.10$ (0.42); $N = 8$
Adaptable	$g = 0.82$ (0.24); $N = 5$	$g = 0.71$ (0.20); $N = 7$
Adaptive + adaptable	$g = 1.18$ ns (0.70); $N = 5$	NA

low prior knowledge are summarized in Table 3. The results imply that for learners with low prior knowledge non-personalized simulation is the most frequently used and yields average effects ($g = 0.68$; $SE = 0.13$). If scaffolding is not personalized, but task progression is adaptable, the effects of simulation are twice as big ($g = 1.37$; $SE = 0.26$) for low prior knowledge learners, suggesting that having control of the task progression combined with non-personalized scaffolding can be particularly beneficial. Fully adaptable simulations for learners with low prior knowledge deliver medium results ($g = 0.52$ ns; $SE = 0.20$), suggesting that some interventions were more effective than others; adaptable scaffolding ($g = 0.27$ ns $SE = 0.06$) with non-personalized task progression is descriptively the least effective condition.

For learners with high prior knowledge non-personalized simulations are also the most frequently used scenario ($g = 0.93$; $SE = 0.10$). If scaffolding is not personalized, but task progression is adaptable, the effects of simulation slightly increase ($g = 1.08$; $SE = 0.25$), but adaptable task progression does not seem that important for learners with high prior knowledge as compared to learners with a low level of prior knowledge. Learners with high prior knowledge can better learn in fully adaptable simulations ($g = 0.92$ ns; $SE = 0.35$), in contrast to learners with low prior knowledge. However, the combination of adaptive scaffolding and adaptable task progression ($g = 2.11$ $SE = 0.45$) is descriptively the most effective scenario for learners with high prior knowledge.

6. Discussion

Prior research has suggested and empirically validated that simulations generally represent effective learning environments to develop complex skills (Chernikova et al., 2020; Belland et al., 2017; Cook et al., 2013). Moreover, simulations – when technology enhanced – provide rich opportunities to personalize learning. This can be done by integrating adaptivity and adaptability in the simulation-based learning environment, both of which are important features when creating and personalizing learning environments. Scaffolding and task progression (navigation) – both adaptive and adaptable – are two possibilities in this regard, which were explored in this meta-analysis.

Based on the literature review, the majority of studies did not implement any adaptive or adaptable strategies to personalize scaffolding (100/143) or task progression (109/162) in simulation-based learning. This can be interpreted as a lack of personalization, especially regarding scaffolding. However, this is only partially surprising: while adaptable task progression can in principle be easily provided in most simulations, adaptive and adaptable scaffolding is usually more difficult to provide as scaffolding measures (adaptive and adaptable conditions) and rules for their deployment must be created, which can be substantially more work (e.g., Nickl et al., 2024). Still, the share of studies using adaptive and adaptable strategies (RQ1) show that innovative approaches allowing better personalization are not sufficiently taken up in research on simulation-based learning. This, in turn is somewhat surprising, as opportunities to adapt scaffolding to learners' needs, knowledge, or performance are considered an essential element of scaffolding (Belland et al., 2017), but might also reflect differences in definitions or in reporting standards.

6.1. *The role of adaptivity and adaptability and their interplay in simulations*

The results for adaptive scaffolding show descriptively high, but also partially significant effects. In contrast, adaptable scaffolding appears to be somewhat less effective and goes along with more variance, possibly as only parts of the learners are able to assess their own need for scaffolding and choose the appropriate amount of scaffolding for themselves, as the available cognitive resources may be limited for these learners. Regarding task progression, effects are descriptively higher for simulations with adaptable task progression, when learners can make decisions about the order of tasks.

Table 3
Prior knowledge and personalization scenarios.

Scaffolding	Task progression			
	Not personalized		Adaptable	
	Low Prior Knowledge	High Prior Knowledge	Low Prior Knowledge	High Prior Knowledge
Not personalized	$g = 0.68$ (0.13); $N = 38$	$g = 0.93$ (0.10); $N = 36$	$g = 1.37$ (0.26); $N = 9$	$g = 1.08$ (0.25); $N = 10$
Adaptive	$g = 0.92$ (0.38); $N = 9$	$g = 1.02$ (0.31); $N = 6$	$g = 0.39$ ns (0.59); $N = 3$	$g = 2.11$ (0.45); $N = 4$
Adaptable	$g = 0.27$ ns (0.06); $N = 2$	$g = 1.33$ (0.06); $N = 2$	$g = 0.52$ ns (0.20); $N = 4$	$g = 0.92$ ns (0.35); $N = 3$
Adaptive+ Adaptable	$g = 1.15$ ns (0.70); $N = 2$	$g = 1.12$ ns (0.88); $N = 4$	NA	NA

While there are only very few studies combining the use of adaptivity and adaptability of scaffolding, the effects are descriptively higher. This may be the case, as the system effectively provides the needed amount of scaffolding and the learners at the same time have an affective-motivational reinforcement, as they perceive higher autonomy and are more engaged in self-regulation (e.g., Wang et al., 2017), which is not the case in the settings where only the system has control over the learning.

6.2. The role of prior knowledge

The results highlight that adaptive scaffolding combined with adaptable task progression show the descriptively largest effects (Table 3). This, for example, can be illustrated in a scenario, where the learner looks for an interesting problem to solve (e.g., selects the task), and if the selected task is too complex for this learner, the system provides the necessary support. However, based on the included studies, this combination of adaptivity and adaptability is only beneficial for learners with high levels of prior knowledge, but not for learners with low prior knowledge. In the case of learners with higher levels of prior knowledge, this may be explained by the provision of effective scaffolding (through reducing extraneous cognitive load) by the system and the affective-motivational reinforcement based on autonomy. The feeling of autonomy might increase intrinsic motivation (e.g., Ryan & Deci, 2000). Furthermore, it might give advanced learners opportunity to select some even more challenging tasks and still get scaffolding from the system if they get lost in those tasks.

In case of learners with lower levels of prior knowledge, this combination of adaptive scaffolding and adaptable task progression was not associated with significant increase in the effects and were descriptively the smallest. As only three quite heterogeneous studies reported this combination of strategies, results need to be interpreted cautiously. Reasons for these results could be a failed adaptation of scaffolding (e.g., due to inadequate learner models), a too complex learning environment (i.e., inadequate intrinsic cognitive load for this level of prior knowledge or overly increased extraneous cognitive load (see Sweller, 2010)), as well as or other factors (e.g., frustration, lack of intrinsic motivation).

In contrast, combinations of adaptable scaffolding and adaptable task progression were associated with descriptively smallest, highly heterogeneous effects for learners with high and low prior knowledge. One of the possible explanations is that the learning environment significantly increased extraneous cognitive load particularly for learners with low prior knowledge, leaving little to no cognitive resources for learning (e.g., Sweller, 2010), as they have to simultaneously monitor both aspects of the learning process (Zimmerman & Moylan, 2009; Zimmerman & Schunk, 2011) and this challenge goes beyond possible effects of autonomy support and engagement in the learning situation.

To summarize, the results underline that as long as students have a certain level of prior knowledge and are familiar with the context, all personalization strategies lead to mostly comparable positive effects. In case of high prior knowledge, the condition of using adaptable scaffolding (i.e., giving learners the opportunity to decide themselves) might under certain circumstances be better than adaptive scaffolding (i.e., decision taken by system based on learners' performance). This may possibly relate to a more accurate self-diagnosis of the learner, as compared to the learner model created by the system, and experiencing the autonomy and own competence by the learner (SDT).

However, if learners have low prior knowledge, adaptable scaffolding conditions show worse effects compared to other, adaptive conditions, which may be related to an extreme increase in extraneous cognitive load (e.g., distributing resources for self-monitoring and deciding about task progression, need in scaffolding) and therefore a decrease in cognitive resources, which learners could have used for actual learning. Furthermore, not only levels of prior knowledge, but also varying levels of SRL skills might strongly affect the effectiveness of personalized instruction (e.g., Dinsmore et al., 2008; Kollar and Fischer, 2006; Seufert et al., 2024), especially if the learners need to make choices concerning scaffolding and task selection. The number of primary studies offering adaptability of scaffolding is low, and conclusions thus need to be made with caution. However, the significance of the effects and the differences in the effects should be considered and further researched.

6.3. Limitations of the study and further research

As mentioned in the discussion, a large part of the studies included in this meta-analysis did not provide sufficient information regarding either adaptivity or adaptability of learning settings, leading to low a sample size for some conditions. Combined with the high heterogeneity of the results due to different definitions and implications for adaptive and adaptable learning, different target outcomes, and settings of the learning environment, this may lead to difficulties in interpreting non-significant findings as well as generalizing the results. It is also worth noticing that most of the studies in the analysis are coming from the field of medical education, and although domain was not found to be a statistically significant moderator, the results can only cautiously be generalized to different contexts and domains of higher education.

Furthermore, this meta-analysis shares a relatively narrow view on adaptability emphasizing learner agency in simulation but not taking into consideration other features of adaptability (e.g., actors' roles during the simulation or human interactors having control over immersive simulations). Therefore, one of the implications for future research should be to include a more systematic description of the learning settings and study design in primary studies (e.g., using adaptivity framework by Plass & Pawar, 2020), as a shared language will facilitate the research and generalizability of further research on adaptability and adaptivity of learning environments. For example, with more systematic descriptions, getting more into technical details of adaptivity implementation (e.g., macro vs. micro level) would become possible.

Another conclusion to be made regarding future research is the need for more primary studies. They might allow the effects of personalization strategies for different learning outcomes and types of simulations. Furthermore, they might enable collecting further evidence by exploring the effects of simulations with adaptive scaffolding (based on learners' performance) and adaptable task progression. In case of learners with low/high prior knowledge, these simulations showed effects of 0.39 vs. 2.11. One of the plausible explanations of the effect might be that learners with low prior knowledge overestimated their competence level in selecting the tasks (task progression). As scaffolding is expected to work in the zone of proximal development (e.g., Vygotsky, 1978), and the selected tasks were outside of this zone, no amount of adaptive scaffolding could compensate for this gap. Alternatively, in the particular primary studies, the scaffolding could have been adapted in non-optimal way, leading to little effects.

It is also important to mention, that this meta-analysis provides some initial insights about effective simulation-based learning environment design, based on research synthesis of previous empirical studies. There are other variables apart from adaptive or adaptable strategies responsible for heterogeneity in the effects of simulation-based learning on learning outcomes. The results do not provide any causal evidence and further primary experimental research is needed to test and validate found associations. Further learner characteristics (interests, goals and motivation; cultural and socio-economic background) as well as contextual factors (e.g., institution policy and curricula, available technology) should be considered. Moreover, another promising direction for research would be to dive deeper into different activities of simulation-based learning (e.g., debriefing phase, see Cheng et al., 2014 for review) and applications of adaptive and adaptable support for these activities.

6.4. Outlook: is generative AI the next frontier in adaptive and adaptable learning?

Emerging technologies, especially within the context of AI, are poised to significantly enhance the landscape of adaptivity and adaptability in simulation-based learning. Among the most recent and promising of these developments is the advent of generative AI models. Unlike traditional algorithms, generative AI is capable of producing content dynamically, drawing from vast amounts of data to tailor instructional content to individual learners. This capability can be transformative for adaptive scaffolding.

More specifically, as learners interact with a simulation, the generative AI can assess their real-time feedback, responses, and progression, adjusting the content or guidance instantaneously to best suit the learner's needs. This means that instructional support can evolve on-the-fly, hence offering learners an experience that is not only consistently aligned with their current proficiency and learning style but eventually also more engaging. Moreover, the potential of generative AI extends beyond adaptivity. By incorporating explicit user input and preferences, generative AI can foster adaptability like no other AI technology was able to achieve before (Chernikova et al., 2020). Learners can be given the autonomy to navigate their learning trajectory, while the AI offers personalized suggestions, resources, or interventions based on its understanding of both the profile and past interactions of and with the learner (Lim et al., 2023).

This allows for more harmonized learning environments, in which system-driven adjustments work together with individual agency. For instance, it could provide insights on which elements of the simulations are best to be presented using adaptable or adaptive strategies at all stages (e.g., training phase or debriefing) during the simulation-based learning process, sensitively depending on a multitude of learner variables beyond prior knowledge.

The confluence of adaptivity and adaptability facilitated by generative AI could potentially lead to a novel learning experience that would not only be responsive to the learner's immediate needs but also empower them to take charge of their own learning journey. However, these opportunities require AI to be trained on sufficient data; furthermore, insights into relevant learning situations are still insufficient.

Santoni de Sio and Mecacci (2021) argue that there are responsibility gaps in systems with artificial intelligence that are rooted in gaps in culpability, moral and public accountability, and active responsibility. The authors propose a solution based on meaningful human control that implies the mapping of agents involved in the AI-based system, their intentions, and their relations to the systems, as well as an analysis of the capacities of the human agents in the system (Santoni de Sio and Mecacci, 2021).

Ethics councils around the world also identified the complexity of the question of responsibility. German Ethics Council emphasizes that responsibility can only be taken by those who develop or implement AI-based technology, by those who facilitate their use or by those who use the technology (Deutscher Ethikrat, 2023). Following these arguments, the simulation developers, therefore, play a central role and take part of the responsibility.

To sum up, besides the powerful capabilities of generative AI itself and the multitude of opportunities contributing to adaptive and adaptable simulation-based learning, it has to be considered that new challenges to use and deal with these opportunities arise (e.g., consideration of and deal with uncertainty or bias). This also opens up completely new research opportunities and affordances, especially in the context of adaptive and adaptable simulation-based learning.

6.5. Implications for research and practice

To further understand the underlying phenomena making personalization effective, the following evidence should be collected and systematized in future research.

1. Measuring variables supporting SRL and SDT (e.g., interest, engagement, meta-cognitive strategies, help-seeking behavior), intrinsic and extraneous cognitive load, and cognitive effort to estimate their moderating role of the effectiveness of learning environments using adaptive and adaptable design and instructional support. Aggregating data from the primary studies.
2. Investigating if the results can be generalized to other learning settings but simulation-based learning environments (e.g., problem-based learning).

3. Investigating opportunities of more precise adaptation of instructional support using AI technologies, and to inform learners to support them making better decisions in adaptable learning environments.
4. Estimating the generalizability of findings to different domains and set of skills

6.6. Conclusion

Personalization can be highly effective in simulation-based learning environments in higher education. It can be achieved through adaptive and adaptable scaffolding and task progression, which have different underlying mechanisms and can be combined to address needs of learners with different levels of prior knowledge. Results underline that it may be beneficial to have adaptive scaffolding, for learners not to miss essential support and guidance (e.g., only some learners are able to choose the right amount of scaffolding). In contrast, different tasks orders can lead to similarly good outcomes in simulations. Navigation is somewhat intrinsic to simulations and – if designed well – different task orders should all lead to positive learning outcomes. Making this adaptability visible to learners by explicitly letting them choose certain aspects of task flow will thus i) not really change the simulation from the cognitive perspective, but ii) allow for higher effects based on affective-motivational perspective.

Personalization is positive as long as learners are in charge of aspects that they are either i) capable of regulating or which are ii) not too critical for their learning in simulations. Providing learners with more control in these cases (through adaptable learning settings) may lead to affective-motivational benefits. We believe that these findings are a promising starting point for systematic research on whether or not these findings still hold when the capabilities of the new generation of AI technologies are used to implement adaptive and adaptable support.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.edurev.2024.100662.

Data availability

Data will be made available on request.

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