

AI-Supported Scenario-Based Learning as Experiential Learning in Higher Education

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Introduction

Professional competence is tested not only by what learners know, but by how they apply that knowledge in professional situations. Before learners enter student teaching, clinical placements, practicums, internships, or other field-based experiences, higher education programs can provide structured rehearsals that prepare them to exercise professional judgment without bearing the full consequences of real-world error. Scenario-based learning helps bridge the gap between remembering and understanding by requiring them to use higher order critical thinking skills to apply knowledge, analyze complex situations, evaluate possible responses, and create or refine solutions in a low-stakes environment. This preparation has often included static digital case scenarios with fixed response options, predetermined feedback, and preprogrammed branching pathways, as well as peer role play or limited opportunities for live practice. These approaches remain valuable, but static scenarios cannot adapt beyond their preprogrammed pathways to individual learner decisions or responses.

Artificial intelligence (AI) is becoming more common within these practice-based environments and in related forms of simulation-based learning. The literature also uses terms such as simulation-based learning, virtual simulation, and AI-supported simulation, particularly when scenarios involve recreated professional settings, virtual agents, simulated patients, or interactive digital environments (Dai & Ke, 2022). Across these forms, learners practice complex skills in professionally relevant contexts rather than only reading about problems, observing experts, analyzing case studies, or completing traditional assessments (Dai & Ke, 2022; Kolb, 1984; Vygotsky, 1978; Zhang et al., 2025; Zheng et al., 2024). AI-supported SBL may make this practice more interactive, responsive, repeatable, and potentially more individualized across

teacher education, medical education, language learning, and professional training (Dai & Ke, 2022; Wei et al., 2025; Younas et al., 2025; Zhang et al., 2025; Zheng et al., 2024).

SBL also connects closely to experiential learning theory. Kolb's model describes learning as a cycle of concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984). Within this framework, a scenario can provide the concrete experience, but experiential learning also depends on opportunities for learners to examine their decisions, connect the experience to disciplinary concepts, and use what they learn to guide subsequent action. SBL therefore aligns most fully with experiential learning when its design supports practice, reflection, conceptual connection, and continued improvement (Kolb, 1984; Kolb & Kolb, 2005; Zheng et al., 2024).

The addition of AI expands the instructional affordances of SBL by broadening the roles that can be built into a scenario. Across the literature, AI systems, including generative artificial intelligence (GenAI), have been used as virtual agents, simulated students, role-play partners, conversational agents, feedback providers, tutors, scenario generators, or assessment support tools (Bai et al., 2024; Dai & Ke, 2022; Shanahan et al., 2023; Zhang et al., 2025). These roles can extend SBL by supporting problem solving, higher-order thinking skills, applied decision-making, and practice with real-world applications (Dai & Ke, 2022; Wei et al., 2025; Zhang et al., 2025; Zheng et al., 2024). However, the value of AI in SBL does not come from novelty alone or from substituting technology for instruction. Its instructional value depends on the role AI plays, how learner interaction is structured, and how learners are supported throughout the experience (Bai et al., 2024; Dai & Ke, 2022; Zhang et al., 2025).

Current research reports several promising outcomes for AI-supported SBL and closely related simulation-based approaches. Studies have connected these environments with

improvements in knowledge acquisition, skill practice, communication, engagement, confidence, learner satisfaction, and student perceptions of the learning experience (Wei et al., 2025; Younas et al., 2025; Zheng et al., 2024). However, this emphasis on whether learners enjoyed, accepted, or benefited from AI-supported learning scenarios leaves an important instructional question unresolved. Less attention has been given to how these environments are actually designed, including the role AI plays, the way learners interact with AI, and the kinds of feedback, prompts, reflection opportunities, or learner support that guide learning (Bai et al., 2024; Chen et al., 2025; Dai & Ke, 2022; Younas et al., 2025; Zhang et al., 2025). As a result, it is difficult to determine whether reported benefits come from the AI itself, the structure of the scenario, the quality of feedback, the opportunity for reflection, or the combination of these elements.

Instructional designers should examine AI-supported SBL environments as designed learning environments rather than simply as activities using advanced technology. Open-ended AI dialogue may create authentic interaction, but it does not necessarily lead to meaningful learning (Dai & Ke, 2022; Shanahan et al., 2023; Zhang et al., 2025). Its instructional value depends on clear learning goals, feedback connected to learner actions, and opportunities for reflection or revision (Brügge et al., 2024; Dai & Ke, 2022; Zhang et al., 2025). A design-focused review can therefore help clarify how AI-supported scenario-based learning interactions are being constructed, what roles AI plays within them, and how interaction, feedback, and support features contribute to experiential learning.

This literature review is guided by the following question: How can the design features and instructional functions of AI-supported scenario-based learning environments described in existing literature be interpreted in relation to the four phases of Kolb's experiential learning cycle in higher education and professional preparation? To address this question, the review

focuses on experiential learning, AI roles, learner–AI interaction, authenticity, feedback, scaffolding, reflection, and reported learning outcomes. These areas are examined in relation to the four phases of Kolb’s experiential learning cycle (Kolb, 1984).

Experiential Learning as a Foundation for Scenario-Based Learning

Experiential learning explains why SBL and related simulation-based approaches can support higher education and professional preparation. Kolb’s theory describes learning as knowledge created through the transformation of experience across concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984). SBL aligns with this cycle because learners act, interpret results, reflect, and use those reflections to inform future decisions.

Scenario-based learning environments are well aligned with this view of learning because they give learners opportunities to engage in authentic problem solving rather than only encounter content in abstract form. In these environments, learners engage with authentic learning tasks that approximate real-world contexts, allowing them to practice reasoning, communication, and decision-making in a lower-risk environment (Dai & Ke, 2022).

Scenario-based eLearning has also been used in higher education to connect disciplinary content with practical and professional applications, supporting active learning, problem solving, and engagement in large cohorts (Mio et al., 2019). For professional preparation, these environments allow learners to develop judgment and skill in complex, contextual situations that are difficult to approximate through lecture or traditional assessment alone.

The experiential value of SBL also connects to situated learning. Lave and Wenger (1991) argued that learning occurs through participation in authentic social and cultural practices. From this perspective, learners develop knowledge not only by receiving information but by

participating in activities that resemble the practices of a field. Scenario-based learning environments can approximate this kind of participation by asking learners to engage in authentic learning tasks, interpret context-specific information, and practice applied decision-making similar to what they may encounter in real-world contexts. By approximating the practices of a field, SBL can connect classroom learning with practice in real-world contexts.

Reflection is also central to the instructional value of SBL. From an experiential learning perspective, learners need opportunities to examine their actions, connect those experiences to concepts, and use those insights to guide future decisions (Kolb, 1984). This process also aligns with Vygotsky's (1978) view that learning can be supported through social interaction and guided reflection. In AI-simulated counseling practice, Akkurt et al. (2025) argued that simulated experiences can become "miseducative" if learners are not guided by clear objectives, structured prompts, learner support, and feedback (p. 2). In SBL more broadly, feedback, prompts, debriefing, and guided reflection can help learners interpret their performance rather than simply complete a task, making reflection a key part of how experience becomes meaningful learning (Dai & Ke, 2022; Zheng et al., 2024).

AI-supported SBL aligns with experiential learning when it provides learners with opportunities to act within a scenario, reflect on their responses, connect experience to concepts, and apply those insights to future decisions (Kolb, 1984; Zheng et al., 2024).

AI-Supported Scenario-Based Learning Across the Experiential Learning Cycle

Organizing the literature around the experiential learning cycle provides a way to examine AI-supported SBL as an instructional design approach. Kolb's model emphasizes movement across concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984). When applied to AI-supported SBL, these phases help

clarify how AI can contribute to learning. AI may support the learner's initial experience, prompt reflection on that experience, help connect the experience to disciplinary concepts, or create opportunities for revised practice. Organizing the literature in this way shifts attention from whether AI is present to how it contributes to the learning process.

Concrete Experience: AI as a Source of Interactive Practice

Within Kolb's cycle, concrete experience refers to the learner's direct encounter with an activity, event, or task that becomes the basis for later reflection and learning (Kolb, 1984). In AI-supported SBL, this phase is often created through interaction with an AI-supported role, case, or scenario element rather than through a static case alone. AI can place learners in a responsive scenario where they must interpret information, respond to changing input, and make applied decisions before moving into reflection or revision.

Several studies illustrate how AI can function as part of the concrete experience itself. AI-powered virtual students have been used to support preservice teachers' practice with classroom discourse and responsive teaching (Zhang et al., 2025). In medical and clinical education, AI-supported problem-based, case-based, and scenario-based learning environments have been used to support learners' practice with diagnosis, clinical reasoning, clinical critical thinking, and applied decision-making (Wei et al., 2025; Zheng et al., 2024). LLM-enabled simulations have also been used in emergency-response training to create caller interactions that approximate real-world contexts and support practice with response procedures in a controlled environment (Chen et al., 2025). In counseling and medical communication education, AI-supported role play and simulated clients or patients have provided opportunities for learners to practice communication, questioning, and response strategies in low-risk conditions (Akkurt et al., 2025; Prazeres, 2025).

Across these examples, AI contributes to concrete experience by giving learners access to practice opportunities that may be difficult to provide consistently through traditional instruction alone (Akkurt et al., 2025; Chen et al., 2025; Dai & Ke, 2022; Zhang et al., 2025). AI-supported SBL can allow learners to repeat an interaction, encounter varied responses, practice with real-world applications, and make decisions without placing actual students, patients, clients, or callers at risk (Akkurt et al., 2025; Chen et al., 2025; Dai & Ke, 2022). The concrete experience becomes instructionally valuable when it provides learners with something substantive to examine, explain, and improve during the later phases of the experiential learning cycle (Kolb, 1984).

Reflective Observation: AI, Feedback, and Guided Reflection

Within Kolb's experiential learning cycle, reflective observation refers to the interpretive work learners do after an experience, as they examine what occurred, consider why it occurred, and begin to make meaning from their actions and decisions (Kolb, 1984). In AI-supported SBL, reflective observation may be supported through instructor-led debriefing, written reflection prompts, AI-generated feedback, interaction transcripts, or structured opportunities to review decisions made during the scenario. Reflection functions as the bridge between participation in the scenario and later conceptual understanding; without opportunities to interpret the experience, learners may complete an interactive task without fully examining the reasoning, assumptions, or decision-making processes that shaped their performance.

The literature on AI-supported learning environments points to feedback and review as central design features in this part of the experiential learning process. Dai and Ke's (2022) systematic mapping review identified feedback, assessment, and learner guidance as prominent applications of AI in simulation-based learning. Brügge et al. (2024) examined structured

feedback in an LLM-based patient simulation and found that medical students who received feedback improved in clinical decision-making compared with students who interacted with the patient simulation alone. This comparison suggests that structured feedback contributed to stronger clinical decision-making performance than simulation alone (Brügge et al., 2024).

Reflection also depends on how the learning activity is structured. In an AI-empowered cardiovascular disease learning environment, Zheng et al. (2024) connected scenario-based activity to Kolb's experiential learning model by incorporating opportunities for students to reflect on their clinical reasoning after working through patient-centered situations. In counseling education, Akkurt et al. (2025) emphasized that AI-simulated practice requires clear objectives, structured prompts, ethical oversight, and feedback so that simulated experience supports learning rather than becoming miseducative. In both contexts, feedback and guided reflection move learners beyond completing the scenario by helping them interpret their actions, recognize gaps in reasoning or performance, and prepare for more informed action in later phases of the experiential learning cycle.

Abstract Conceptualization: Connecting Scenario Experience to Disciplinary

Understanding

The third phase of Kolb's experiential learning cycle, abstract conceptualization, involves forming concepts, explanations, or generalizations from reflected experience (Kolb, 1984). In AI-supported SBL, this phase concerns the movement from scenario participation to disciplinary understanding. After learners interact with an AI-supported case, patient, student, client, or problem situation, they must connect that experience to the concepts, frameworks, procedures, or reasoning processes that define competent practice in a field. From an experiential learning perspective, scenario participation becomes more instructionally meaningful when learners

connect the experience to concepts, frameworks, or principles that can inform future action (Kolb, 1984; Kolb & Kolb, 2005; Shen et al., 2026). In AI-supported designs, this conceptual work may be supported through prompts, feedback, or task structures that require learners to explain how disciplinary concepts apply to the scenario rather than simply accept AI-generated explanations or recommendations (Montoya-Torres, 2026; Shen et al., 2026; Zheng et al., 2024).

In medical and clinical education, abstract conceptualization is reflected in the way learners use disciplinary knowledge to interpret patient information and reason through clinical problems. Wei et al. (2025) reported that AI-supported problem- and case-based learning in medical and dental education has been associated with knowledge acquisition and clinical reasoning. Zheng et al. (2024) also illustrate this conceptual movement in clinical education, as students used cardiovascular disease knowledge to interpret patient information and connect scenario details to clinical reasoning and decision-making. In this type of design, AI-supported interaction is not simply a “practice” opportunity. It also becomes a setting where learners connect patient information, clinical knowledge, and disciplinary concepts.

Beyond clinical education, AI-supported experiential learning environments also show how abstract conceptualization can occur through modeling, design, and problem formulation. Montoya-Torres (2026) described generative AI as a support for experiential learning in systems engineering, where learners moved from applied scenarios and data to identifying variables, constraints, models, and solution strategies. Al-Jazzar (2026) connected AI-supported design pedagogy to experiential learning by showing how learners used AI during ideation and redesign activities. In these examples, abstract conceptualization involves using the scenario or design problem as a basis for developing explanations, recognizing patterns, applying frameworks, and preparing knowledge for future use.

Because AI can generate explanations, summaries, or recommendations without necessarily requiring learners to develop their own conceptual understanding, those outputs cannot function as the endpoint of learning. Learners need structured opportunities to interpret the scenario through disciplinary concepts, examine the reasoning behind their decisions, and connect the experience to principles or frameworks that can guide future action (Kolb, 1984; Montoya-Torres, 2026; Shen et al., 2026; Zheng et al., 2024).

Active Experimentation: Revised Practice and Future Application

The fourth phase of Kolb's experiential learning cycle, active experimentation, involves using what has been learned from prior experience, reflection, and conceptualization to guide future action (Kolb, 1984). In AI-supported SBL, this phase may occur when learners revise a response, attempt a scenario again, test a different strategy, or apply what they learned to a new case or problem situation (Kolb, 1984; Shen et al., 2026). Active experimentation extends learning beyond a single scenario by using feedback, reflection, and conceptual understanding to shape subsequent decisions (Kolb, 1984).

AI-supported SBL may make repeated or varied practice more feasible (Chen et al., 2025; Dai & Ke, 2022; Li & Lebai Lutfi, 2026). In active experimentation, however, repetition is instructionally meaningful when learners use feedback or prior experience to test an adjusted approach. Brügge et al. (2024) illustrate this process: medical students completed multiple AI-simulated patient encounters, and those who received structured feedback demonstrated stronger clinical decision-making performance than the simulation-only group.

Active experimentation also connects closely to questions of transfer. Shen et al. (2026) noted that far transfer, long-term retention, and interpersonal dimensions of practice remain understudied in research on AI-supported clinical reasoning training. Repeated interaction should

therefore be treated as an opportunity for practice, not as evidence of transfer. Transfer must be demonstrated when learners apply what they learned in a new or more complex context (Shen et al., 2026). Designs that aim to support active experimentation should therefore include revised strategies, varied scenarios, or later tasks that require learners to apply conceptual understanding beyond the original activity (Kolb, 1984; Shen et al., 2026).

Within this phase, the central design question is whether learners use feedback and conceptual understanding to improve a later response or apply their learning in a different situation. AI can make revision and repeated practice more feasible, but the design must include a genuine opportunity for subsequent action rather than ending with the original scenario (Dai & Ke, 2022; Kolb, 1984; Shen et al., 2026).

Learner–AI Interaction and Authenticity

The effectiveness of AI-supported SBL also depends on the quality of the learner–AI interaction. Across the literature, AI-supported conversational roles can make scenarios more responsive than static cases by requiring learners to interpret and adjust to simulated students, clients, patients, callers, or other role-play partners as the interaction unfolds (Akkurt et al., 2025; Chen et al., 2025; Dai & Ke, 2022; Li & Lebai Lutfi, 2026; Shanahan et al., 2023; Zhang et al., 2025). However, conversational responsiveness should not be treated as the same thing as authenticity (Akkurt et al., 2025; Li & Lebai Lutfi, 2026; Prazeres, 2025; Shanahan et al., 2023). An AI-generated interaction may appear interactive while still lacking the emotional nuance, contextual complexity, or disciplinary accuracy needed to support meaningful professional practice.

Akkurt et al. (2025) illustrate this tension in counseling education. Counselor trainees viewed ChatGPT as a psychologically safe and flexible supplement for practicing counseling

skills before working with real clients. At the same time, the study emphasized the need for structured prompts, ethical oversight, and attention to realism. The simulated client experience was useful not because ChatGPT replaced human practice, but because it gave learners a low-risk space to rehearse counseling interactions while still requiring instructional boundaries and human judgment. In this context, authenticity depended not only on whether ChatGPT could produce a plausible client response, but on whether the interaction aligned with the goals, expectations, and ethical demands of counseling practice.

This concern extends to other AI-supported role-play and simulation environments. Shanahan et al. (2023) explain LLM role play as prompted language behavior rather than human understanding, underscoring the importance of role design and conversational framing. In medical education, Li and Lebai Lutfi (2026) found that LLM-based virtual patient systems offer scalable opportunities for history-taking practice, but also identified concerns related to quality, hallucination, fairness, and inconsistent evaluation. Using a simulated single-case study, Prazeres (2025) explored whether ChatGPT could help general practitioners rehearse conversations with patients who are dying, while also noting limitations in directness and cultural responsiveness. Rather than treating conversational responsiveness as sufficient, this literature frames authenticity as a design problem. The simulated role, learner task, professional standards, and known limitations of AI-generated dialogue must be considered in how the interaction is designed, bounded, and evaluated.

Authenticity in AI-supported SBL should therefore be understood as a design achievement rather than an automatic feature of AI. A scenario may feel conversational while still requiring clear objectives, role constraints, feedback mechanisms, and human oversight to align the interaction with disciplinary practice (Akkurt et al., 2025; Dai & Ke, 2022; Li & Lebai

Lutfi, 2026; Shanahan et al., 2023). Without these elements, an engaging interaction may remain only loosely connected to the intended learning goals.

Reported Learning Outcomes of AI-Supported SBL

Research on AI-supported SBL presents a promising but uneven range of outcomes, including knowledge acquisition, reasoning, communication practice, engagement, confidence, and learner satisfaction (Wei et al., 2025; Younas et al., 2025; Zheng et al., 2024). Because these outcomes are measured differently across studies, they should not be treated as equivalent evidence of learning.

In clinical and health professions education, reported outcomes often center on knowledge, reasoning, and decision-making. Wei et al. (2025) found significant knowledge gains and high learner satisfaction, while clinical-reasoning results were mixed but generally favorable and could not be statistically pooled because of methodological and measurement differences. Zheng et al. (2024) reported higher theoretical knowledge, clinical skills, and clinical critical thinking outcomes among students who participated in an AI-empowered cardiovascular disease scenario-based learning environment. Brügge et al. (2024) also found that medical students who received structured feedback after interacting with LLM-based patient simulations improved in clinical decision-making compared with students who interacted with the patient simulation alone. Among these studies, Brügge et al. (2024) provide the clearest evidence that structured feedback contributed to stronger performance than simulation alone.

Other studies emphasize communication, confidence, and learner perceptions. Akkurt et al. (2025) found that counselor trainees viewed ChatGPT as a psychologically safe and flexible supplement for practicing counseling skills before working with real clients. Kapráliková and Novák (2025) described AI-powered business negotiation simulations as supporting strategic

awareness, emotional framing, and self-regulated learning. In university-level English instruction, Younas et al. (2025) reported positive learner responses to AI-generated scenario-based teaching, including engagement and satisfaction. In these contexts, reported benefits centered primarily on psychologically safe practice, strategic awareness, confidence, engagement, or learner satisfaction rather than direct evidence of transfer (Akkurt et al., 2025; Kapráliková & Novák, 2025; Younas et al., 2025).

Research examining transfer remains limited. Shen et al. (2026) found that most studies focused on knowledge gains and near transfer, while far transfer, long-term retention, and interpersonal dimensions of professional practice received much less attention. Current findings suggest that AI-supported SBL may improve performance within designed learning environments or on closely related tasks, but the limited literature leaves unanswered whether those gains persist over time or extend to more distant, complex professional contexts. Reported outcomes should therefore be interpreted in relation to the type of assessment used and the distance between the learning task and the transfer context.

Limitations and Design Considerations

AI-generated dialogue may introduce hallucinations, inconsistent responses, factual inaccuracies, or behavior that does not align with the intended professional context (Li & Lebai Lutfi, 2026). Shanahan et al. (2023) explain that LLM role play reflects prompted language behavior rather than human understanding, so plausible dialogue should not automatically be treated as a dependable representation of disciplinary practice. When learners use these interactions as a basis for professional reasoning, role constraints, source grounding, validation, and human review become important design safeguards (Bai et al., 2024; Li & Lebai Lutfi, 2026; Shanahan et al., 2023).

The limitations of AI-generated interaction extend beyond factual accuracy. Counselor trainees in Akkurt et al. (2025) described ChatGPT as useful for psychologically safe practice while also noting overly agreeable responses and limited emotional and cultural specificity. In a simulated single-case study, Prazeres (2025) explored ChatGPT-supported rehearsal with general practitioners and found that the interaction did not fully address cultural or religious dimensions of conversations with patients who were dying. These findings show why AI-generated dialogue should be evaluated for emotional, cultural, and contextual adequacy rather than conversational fluency alone.

Methodological limitations also constrain conclusions about learning outcomes. Li and Lebai Lutfi (2026) identified small samples, inconsistent evaluation methods, and limited comparability across studies of LLM-based virtual patients. Positive findings should therefore be interpreted in relation to what was measured, when it was measured, and how closely the assessment resembled the original learning activity, especially because evidence for sustained or more distant transfer remains limited (Shen et al., 2026).

These limitations make instructor judgment and human oversight part of the instructional design rather than simply serving as technical safeguards. Clear learning objectives, bounded AI roles, grounding in approved content, expert review, and structured feedback should be established before learners rely on the simulation for professional reasoning (Akkurt et al., 2025; Bai et al., 2024; Dai & Ke, 2022; Li & Lebai Lutfi, 2026). Reflection, conceptual connection, and revision must also be designed as learner activities rather than assumed to occur because the interaction is engaging (Kolb, 1984).

Summary

The literature describes AI-supported SBL as a collection of designed learning environments in which AI may function as a simulated person, feedback provider, or source of instructional support (Dai & Ke, 2022; Shanahan et al., 2023; Zhang et al., 2025). Its contribution depends on how these roles are integrated into the learning activity and connected to disciplinary goals, learner decision-making, and opportunities for continued learning.

Organizing the literature through Kolb's experiential learning cycle clarifies how AI-supported SBL can contribute beyond the initial interaction. AI may support concrete experience through responsive practice, reflective observation through feedback and review, abstract conceptualization through connections to disciplinary concepts, and active experimentation through revision, repeated practice, or application to new situations (Kolb, 1984). AI-supported SBL is therefore most closely aligned with experiential learning when the design supports movement across these phases rather than ending with the initial interaction.

Reported outcomes include knowledge gains, reasoning, clinical reasoning, communication practice, confidence, engagement, and learner satisfaction (Akkurt et al., 2025; Brügge et al., 2024; Wei et al., 2025; Younas et al., 2025; Zheng et al., 2024). However, these findings remain uneven. Within the literature reviewed, most evidence concerns immediate learning and near transfer, while studies examining far transfer, long-term retention, or performance in complex professional settings remain scarce (Shen et al., 2026; Wei et al., 2025). Questions also remain about the authenticity, accuracy, consistency, emotional nuance, and cultural responsiveness of AI-generated interactions, particularly when learners rely on simulated clients or patients as representations of professional practice (Akkurt et al., 2025; Li & Lebai Lutfi, 2026; Prazeres, 2025).

The instructional value of AI-supported SBL lies in the design of the learning environment surrounding it (Dai & Ke, 2022; Kolb & Kolb, 2005). Conversational fluency, responsiveness, and repeatability can expand opportunities for practice, but they do not by themselves ensure meaningful experiential learning (Akkurt et al., 2025; Li & Lebai Lutfi, 2026; Shanahan et al., 2023). The effectiveness of an AI-supported scenario relies on a holistic design approach in which a collage of interdependent factors works together to support a coherent experiential learning process. These factors include clear objectives, bounded AI roles, disciplinary alignment, feedback, reflection, conceptual connection, revised practice, and human oversight (Akkurt et al., 2025; Dai & Ke, 2022; Kolb, 1984; Kolb & Kolb, 2005; Li & Lebai Lutfi, 2026). Viewed through this lens, AI-supported SBL offers considerable potential for higher education and professional preparation, but that potential hinges upon how deliberately the technology is situated within the learning environment to support the full experiential learning process (Kolb, 1984; Kolb & Kolb, 2005; Zheng et al., 2024).

References

- Akkurt, M., Maurya, R., & Brown, T. (2025). Learning through simulation: Counselor trainees' interactions with ChatGPT as a client. *Behavioral Sciences*, 15(12), Article 1660.
<https://doi.org/10.3390/bs15121660>
- Al-Jazzar, F. H. (2026). AI-driven design pedagogy in packaging redesign: Integrating experiential learning and creativity. *Innovations in Education and Teaching International*, 1–19. <https://doi.org/10.1080/14703297.2026.2671794>
- Bai, S., Gonda, D. E., & Hew, K. F. (2024). Write–curate–verify: A case study of leveraging generative AI for scenario writing in scenario-based learning. *IEEE Transactions on Learning Technologies*, 17, 1313–1324. <https://doi.org/10.1109/TLT.2024.3378306>
- Brügge, E., Ricchizzi, S., Arenbeck, M., Keller, M. N., Schur, L., Stummer, W., Holling, M., Lu, M. H., & Darici, D. (2024). Large language models improve clinical decision making of medical students through patient simulation and structured feedback: A randomized controlled trial. *BMC Medical Education*, 24, Article 1391.
<https://doi.org/10.1186/s12909-024-06399-7>
- Chen, Z., Chason, E., Mladenovski, N., Wilson, E., Mullen, K., Martini, S., & Ma, M. (2025). Sim911: Towards effective and equitable 9-1-1 dispatcher training with an LLM-enabled simulation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(27), 27896–27904. <https://doi.org/10.1609/aaai.v39i27.35006>
- 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, 100087. <https://doi.org/10.1016/j.caeai.2022.100087>
- Dai, C.-P., & Ke, F. (2026). Model-based support for teaching practice and self-efficacy in

- artificial intelligence-enhanced virtual reality teaching simulation. *Educational Technology Research and Development*. Advance online publication. <https://doi.org/10.1007/s11423-026-10592-4>
- Kaprálíková, I., & Novák, D. (2025). AI-powered simulations for business negotiations: Enhancing skill development through technology. *CASALC Review*, 15(2), 44–74. <https://doi.org/10.5817/CASALC2025-2-3>
- Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Prentice-Hall.
- Kolb, A. Y., & Kolb, D. A. (2005). Learning styles and learning spaces: Enhancing experiential learning in higher education. *Academy of Management Learning & Education*, 4(2), 193–212. <https://doi.org/10.5465/amle.2005.17268566>
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.
- Li, D., & Lebai Lutfi, S. (2026). Large language model–based virtual patient systems for history-taking in medical education: Comprehensive systematic review. *JMIR Medical Informatics*, 14, e79039. <https://doi.org/10.2196/79039>
- Mio, C., Ventura-Medina, E., & João, E. (2019). Scenario-based eLearning to promote active learning in large cohorts: Students’ perspective. *Computer Applications in Engineering Education*, 27(4), 894–909. <https://doi.org/10.1002/cae.22123>
- Montoya-Torres, J. R. (2026). Experiential learning meets generative AI: Teaching quantitative methods in systems engineering. In *Proceedings of the 15th International Conference on Operations Research and Enterprise Systems (ICORES 2026)* (pp. 510–515). SCITEPRESS. <https://doi.org/10.5220/0014565100004055>

- Prazeres, F. (2025). Can ChatGPT help general practitioners become acquainted with conversations about dying? A simulated single-case study. *Healthcare*, 13(7), Article 835. <https://doi.org/10.3390/healthcare13070835>
- Shanahan, M., McDonell, K., & Reynolds, L. (2023). Role play with large language models. *Nature*, 623(7987), 493-498. <https://doi.org/10.1038/s41586-023-06647-8>
- Shen, S., Qi, W., Zeng, J., Li, S., Liu, X., Feng, Y., & Cao, S. (2026). Does AI-supported clinical reasoning training enhance learning transfer in nursing students? A systematic review and narrative synthesis. *Nurse Education in Practice*, 93, Article 104799. <https://doi.org/10.1016/j.nepr.2026.104799>
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Wei, H., Dai, Y., Yuan, K., Li, K. Y., Hung, K. F., Hu, E. M., Lee, A. H. C., Chang, J. W. W., Zhang, C., & Li, X. (2025). AI-powered problem-and case-based learning in medical and dental education: A systematic review and meta-analysis. *International Dental Journal*, 75(4), 100858. <https://doi.org/10.1016/j.identj.2025.100858>
- Younas, M., Ismayil, I., El-Dakhs, D. A. S., Anwar, B., & Noor, U. (2025). Evaluating the effectiveness of digital scenario-based English teaching at the university level using artificial intelligence-generated content. *Frontiers in Education*, 10, 1670892. <https://doi.org/10.3389/feduc.2025.1670892>
- Zhang, N., Ke, F., Dai, C.-P., Southerland, S. A., & Yuan, X. (2025). Seeking to support preservice teachers' responsive teaching: Leveraging artificial intelligence-supported virtual simulation. *British Journal of Educational Technology*, 56(3), 1148–1169. <https://doi.org/10.1111/bjet.13522>

Zheng, K., Shen, Z., Chen, Z., Che, C., & Zhu, H. (2024). Application of AI-empowered scenario-based simulation teaching mode in cardiovascular disease education. *BMC Medical Education*, 24, 1003. <https://doi.org/10.1186/s12909-024-05977-z>

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