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A Comparative Case Study of AI-Enabled and Traditional Experiential Simulations in Operations and Supply Chain Education

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Abstract

This study presents a comparative case study examining differences in the pedagogical impact between an AI-enabled negotiation simulation and a traditional non-AI 5S (Sort, Set in Order, Shine, Standardize, Sustain) lean simulation on students' conceptual understanding, reflective thinking, and perceived usefulness. The AI-enabled simulation was implemented in an undergraduate Operations and Supply Chain Management (OSCM) course and designed to engage students across all four stages of Kolb's experiential learning cycle through iterative negotiation rounds with an AI-simulated supplier, while a traditional non-AI 5S simulation served as a conventional experiential benchmark. Using a qualitative-dominant mixed-methods case study approach, data were collected from students' reflection reports, discussion posts, peer responses, and a post-assignment perception survey. Findings indicate that student artifacts associated with the AI-enabled simulation, compared to those from the 5S simulation, reflected higher levels of conceptual understanding and cognitive engagement. However, students' perceived usefulness and value were lower for the AI-enabled activity. Compared with the 5S simulation, the AI-enabled activity required more complex tasks. Although it was associated with deeper understanding and insight, students tended to rate easier tasks as more useful. These mixed results reveal a gap between subjective perceptions and objective learning outcomes and underscore the importance of instructional design that incorporates desirable difficulties. This study contributes to OSCM pedagogy by offering evidence-based insights from a single-course implementation into how technology-enhanced experiential learning may support the development of both technical and durable skills while maintaining theoretical coherence and instructional rigor.

Keywords: Experiential Learning, Kolb's Experiential Learning Theory, AI-Enabled Simulation, Operations and Supply Chain Education, Cognitive Engagement, Generative AI

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A Comparative Case Study of AI-Enabled and Traditional Experiential Simulations in Operations and Supply Chain Education

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1. INTRODUCTION

Generative AI tools are widely available, raising a pressing question on how to integrate them into education to make teaching and learning more effective. While educators see the benefits, challenges remain in how to incorporate AI tools into education properly and responsibly to maximize its advantages and minimize potential risks such as plagiarism and misinformation (Kurtz et al., 2024; The Oxford University Press, 2023; Tu, 2024; Wang et al., 2024).

In parallel, the rapid evolution of AI is transforming the labor market, compelling education systems to adapt accordingly. Recent research shows that since 2019, the demand for AI-related skills has been growing at a rate of 21% (Bain, 2025). Equally important, human skills, such as creative thinking, adaptability, and ethical judgment, continue to rise in importance (The World Economic Forum, 2025). Within this evolving landscape, organizations globally face significant challenges in finding talent with the optimal combination of technical and durable human skills (LinkedIn, 2025). These trends raise a critical question: how can we effectively and responsibly integrate AI tools into classroom teaching and learning to equip students with the right mix of those skills?

Prior research on AI integration in education advocates fundamental shifts from traditional passive models toward student-centered approaches that promote active engagement and critical thinking (Kurtz et al., 2024; Muscanell & Robert, 2023; Raptis, 2024). Several studies highlight the role of generative AI as a collaborative learning partner in supporting self-directed learning while requiring students to evaluate information and formulate subsequent prompts (Aladsani, 2025; Raptis, 2024). Rather than viewing AI as a threat, education should strategically utilize AI tools to facilitate interactive and dynamic engagement with educational materials (Association to Advance Collegiate Schools of Business [AACSB], 2023).

Given this emphasis on preparing students for AI-driven work environments, OSCM offers a compelling context for experiential AI integration. Recent work suggests that AI-supported instructional activities can enhance student engagement and learning when combined with structured guidance and validation tools (Li & Ho, 2024). Shalpegin and Nguyen (2024) argue that incorporating AI education provides opportunities for students to develop skills in technology and automation and offers innovative ways for students to strengthen their AI adaptation and application in the professional world.

In parallel, supply chain management education research argues that students benefit when learning experiences connect conceptual knowledge with real-world application and industry-relevant problem solving (Baveja et al., 2024). Poo and Qi (2023) similarly suggest that AI technologies, such as machine learning algorithms, optimization models, and simulation tools, provide an opportunity for increasing the impact and significance of the quality and effectiveness of laboratory experiments and thereby implicitly impact teaching. They conclude that the AI-powered class sessions empower students with an innate understanding of real-world supply chain challenges. Together, these studies suggest that AI-enabled instructional design may strengthen students' understanding of core OSCM concepts while also supporting the development of practical decision-making skills.

From a corporate perspective, AI and machine learning are increasingly recognized as strategic assets in OSCM, driving improvements across demand forecasting, inventory optimization, and operational execution (Çaylı & Oralhan, 2024; Kumar et al., 2024; Meyer et al., 2021; Mohsen, 2023). However, AI tools are only effective when professionals can interpret and act on their insights (Abhulimen & Ejike, 2024; de la Roche et al., 2024; Forbes, 2025). To address the growing skills gap, organizations are investing in equipping employees to work effectively with AI technologies (Cardon, 2023). Despite these investments, there is still limited research on how AI-based learning activities affect students' level of reflective thinking and understanding of key concepts in OSCM education.

Building on the workforce's need for both AI literacy and domain-specific skills, this study introduces an AI-Enabled Negotiation Simulation (referred to as "AI simulation"), compares it with a non-AI 5S Lean Simulation (referred to as "5S simulation") within an undergraduate OSCM course. The study examines how students' reflective thinking, conceptual understanding, and perceptions differ across these two experiential learning activities. The following research questions guide this inquiry:

- *RQ1: In what ways is the AI simulation associated with student engagement in the learning process, particularly in terms of their cognitive effort and reflective thinking?*
- *RQ2: How is the AI simulation associated with the depth and quality of students' conceptual understanding?*
- *RQ3: How do students evaluate the AI simulation compared to the 5S simulation?*

2. THEORETICAL FRAMEWORK

Kolb's Experiential Learning Theory (ELT) is a useful framework to model a continuous and holistic learning cycle of a student. Kolb (1984) described learning as a dynamic process of grasping experiences and transforming them into knowledge through four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation. This cyclical process, shown in Figure 1, begins with concrete experience, where learning occurs through doing or observing in real or simulated contexts such as fieldwork, labs, or simulations. In reflective observation, students consciously analyze these experiences, often using brainstorming, discussion, or personal journaling; In abstract conceptualization, they develop theories, models, or hypotheses based on their reflections, drawing meaning from their experiences through logic and analysis; In active experimentation, students test these ideas by planning and applying them in new contexts, which may include further labs, fieldwork, projects, or case studies (Akella, 2010; Bergsteiner et al., 2010; Botelho et al., 2016).

The ELT's dynamic and cyclical nature is well suited to modeling a student's learning of complex, nonlinear phenomena (Botelho et al., 2016). Learning from concrete experience requires active and critical reflection by observing, a student's effort to understand their experience, followed by the conceptualization of a theory or hypothesis by thinking (Botelho et al., 2016). The continuous process will test this theory, which is connected to another concrete experience (Bell & Bell, 2020; Fewster-Thuente & Batteson, 2018).

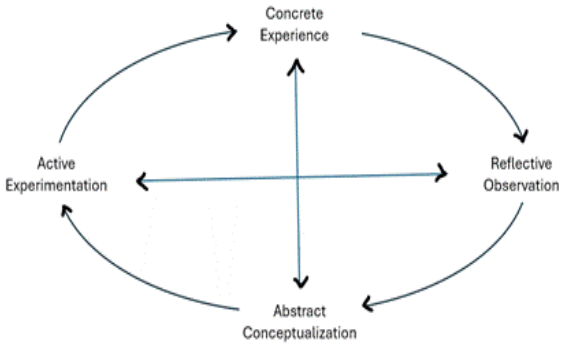


Figure 1: Kolb's Experiential Learning Framework

Note. From *Experiential Learning: Experience as the Source of Learning and Development (p. 21), by D. A. Kolb, 1984, Prentice-Hall. Copyright 1984 by Prentice-Hall.*

Kolb's ELT has been extensively utilized in various fields of education (Bell & Bell, 2020; Botelho et al., 2016; Fewster-Thuente & Batteson, 2018; Turesky & Wood, 2010; Wijnen-Meijer et al., 2022), especially with the application of simulations. This theory also aligns closely with the fundamental transformation of teaching and learning in the age of AI, as both emphasize student-centered approaches that promote self-directed learning while fostering interactive and dynamic cognitive engagement with educational content. In this study, the terms "engagement" and "cognitive engagement" are used interchangeably and refer to the mental effort and strategic thinking students invest in learning tasks (Fredricks, Blumenfeld, & Paris, 2004). The key elements of ELT theory that demonstrate this alignment include the following (Kolb & Kolb, 2009; Morris, 2020):

- Learning is grounded in experience. The AI simulation provides an ideal environment for students to develop a stronger sense of themselves as learners by negotiating procurement contracts with an AI supplier. This activity immerses students through four stages in the ELT model.
- Metacognitive capabilities involve learners' awareness of their learning processes, recognition of challenges, and strategies for improving learning. The AI simulation supports the development of these capabilities by prompting students to identify obstacles and reflect on ways to enhance their learning.
- Learning is a cyclical process, where concrete experiences are continuously enriched through reflection, conceptualization, and active

experimentation. The AI simulation reinforces this cycle, as reaching an agreement typically requires multiple negotiation rounds. Each round builds on the previous one, a spiral of increasingly sophisticated understanding.
- The effectiveness of experiential learning depends on context. The AI simulation provides a rich, discipline-specific environment that reflects real-world negotiation challenges in OSCM. This context informs students' experiences, sharpens their conceptual thinking, and shapes how they perceive and internalize what they learn.

To examine how these experiential learning elements unfold in practice, this study used a qualitative case study approach to compare two simulations (i.e., AI simulation and 5S simulation) and explored how student learning was expressed within the AI simulation context.

3. METHODOLOGY

Research Design

This study adopts a qualitative-dominant mixed-methods case study design. According to Baxter and Jack (2008), the qualitative case study provides guidance for developing clear research questions and the focus of the study, emphasizes theoretically informed propositions to guide data collection and analysis, stresses the importance of "binding the case" for what will and will not be studied, and requires multiple sources of evidence to support triangulation and strengthen the study's credibility. In this study, qualitative analysis of student reflections and discussion artifacts serves as the primary analytical approach, complemented by quantitative summaries and statistical comparisons to support the interpretation of patterns across simulation activities and students' perceptions.

Combined with Kolb's experiential learning theory, this research design placed students in authentic contexts where they could develop and apply critical thinking, problem-solving, negotiation, and prompt engineering skills. This methodological design ensured that the research questions regarding student learning processes and experiences were explored holistically, in line with the study's aim to understand how AI tools influence applied OSCM education. The study remained bounded within the scope of a single undergraduate OSCM course with clearly defined assignments, aligning with Baxter and Jack's (2008) guidance for maintaining a focused case. Two simulations (AI simulation and 5S simulation) generated rich qualitative data through individual reflection reports, Blackboard discussion posts, and peer replies. These qualitative data were systematically coded and analyzed, with coding frequencies, average scores, and statistical comparisons used to examine differences between the two simulations. These multiple data sources enabled triangulation and supported a credible chain of evidence (Table 1).

RQ	Data Source	Outcome Measures	Analytical Approach
RQ1: Cognitive engagement effort and reflective thinking	Reflection reports Discussion posts/replies	Reflective Insights	Thematic coding; Frequency and average comparisons; ANOVA and T-Test
RQ2: Depth and quality of conceptual understanding	Reflection reports Discussion posts/replies	Conceptual understanding	Thematic coding; Frequency and average comparisons; ANOVA and T-Test
RQ3: Student perceptions	Post-assignment survey	Perceived usefulness and value	Descriptive statistics (distribution of ratings)

Table 1: Research Design Alignment

Participant Recruitment

This study was conducted in a private urban university in the northeastern United States. Participants included 40 students enrolled in an introductory course on OSCM, which is part of the business core curriculum. The sample represented students from both business-related and non-business majors. The participants were sophomores, juniors, and seniors.

Of the 40 students enrolled in the course, 11 were excluded from the analysis due to incomplete submissions, defined as missing one or more required components (e.g., reflection report, discussion post, or peer reply) across the simulation activities. Only students with complete data across all evaluated components were included to ensure consistency in coding and comparison. A comparison of respondent and non-respondent distributions by major and class indicates noticeable differences (Appendix A), suggesting the possibility of non-response bias. For example, finance majors comprised a larger proportion of respondents but were not represented among non-respondents. In terms of class standing, sophomore students represented

a larger portion of respondents than in the non-respondent group. Due to the small sample size and uneven group distributions, these observations are descriptive and should be interpreted with caution.

Data Collection

The data were collected through two simulation assignments and a post-assignment survey. Both simulations followed an experiential learning approach to actively engage students with OSCM concepts. The key difference was that one simulation integrated AI while the other did not, allowing for a comparison of differences in engagement and perceived learning.

The AI simulation, conducted in week 9 as part of the inventory management chapter, used a generative AI tool (ChatGPT or Copilot) to integrate inventory cost analysis with procurement negotiation techniques. This assignment combined technical skills (e.g., cost modeling) with durable skills (e.g., negotiation, communication, and problem-solving). Students first reviewed how to compare ordering policies and how purchasing terms affect inventory costs, then engaged in multiple negotiation rounds with an AI-simulated supplier. In the negotiation process, students assumed the role of a procurement manager, proposed contract terms, received counteroffers from the AI acting as the supplier, and iteratively refined their negotiation strategies through successive exchanges. Students were also required to document key negotiation rounds, including prompts, counter offers, and final agreements, as part of their reflection. Sample prompts and negotiation guidance (e.g., order quantity, price, and contract terms) were provided to support student interaction with the AI tool. For this simulation, each student submitted an individual reflection report, posted key results and strategies on a Blackboard discussion board, and replied to another student's post.

The 5S simulation, conducted in week 11 as part of the Lean and Six Sigma chapter and hosted on a traditional website, helped students internalize the core Lean principles: Sort, Set in Order, Shine, Standardize, and Sustain (Randhawa & Ahuja, 2017). Through an interactive online game (5S Alphabet Game, 2014), students completed simple sorting and error-finding tasks across six scenarios, experiencing incremental improvements in task efficiency. For this activity, students posted their simulation results and a brief reflection on the discussion board, along with a reply to a classmate's post.

The AI simulation was completed two weeks prior to the 5S simulation and was embedded in a different course chapter, reducing the likelihood of direct knowledge carryover between tasks. However, the study does not include a separate control group or randomized assignment, as all students completed both simulations as part of the course requirements. In addition, no pre-assignment baseline measures were collected. Therefore, the findings should be interpreted as comparative insights within a single-course implementation rather than causal evidence of the effectiveness of AI-enabled versus non-AI simulations.

In addition, a post-assignment survey designed by the instructor and administered at the end of the semester collected student numerical ratings on "perceived usefulness and value" of each simulation assignment. Students evaluated how much they liked each assignment, considering how interesting it was and how much it helped them understand OSCM concepts (Appendix B).

Data Coding Procedure

For qualitative data, such as the reflection reports, discussion posts, and peer replies, a thematic analysis was conducted. This widely used method in qualitative research helps to identify, analyze, and interpret patterns (or "themes") (Braun & Clarke, 2006), making it well-suited for exploring students' learning experiences and perceptions in an educational context.

The coding process began with an initial structure consisting of two broad themes: cognitive and reflective processes and conceptual understanding. Each theme was defined across multiple performance levels, with level 0 representing no meaningful or relevant engagement while level 3 indicating the highest level of involvement. Through careful review of students' reflection reports, discussion posts, and peer replies, relevant keywords were identified, grouped into categories, and aggregated into thematic patterns. These themes were iteratively refined and formalized into a structured set of coding dimensions: *Reflective Insight* and *Conceptual Understanding*. At the same time, the rubric definitions for each performance level were refined to support consistent evaluation. Each student response was evaluated based on the presence, depth, and integration of relevant concepts and reasoning processes. The final coding schema and its detailed rubric are presented in Section 4 and Appendix C.

When responses did not clearly align with a specific performance level within a coding dimension, decisions were made by referencing the rubric definitions to ensure consistent interpretation across submissions. For example, a response that connected negotiation outcomes to inventory cost trade-offs and explained how adjusting order quantity reduced holding costs while maintaining supplier agreement was coded as level 3 in Conceptual Understanding. In contrast, a response that merely described the negotiation outcome without explaining the underlying reasoning was coded as level 1. Similarly, for Reflective Insight, a response that identified challenges, proposed alternative strategies (e.g., payment terms or credits), and explained how these contributed to the outcome was coded as level 3. In contrast, a response that provided only a general statement of the outcome without explanation or reflection was coded as level 1.

Due to the nature of the data collected, the coding was conducted solely by the course instructor, in accordance with the IRB exemption granted for this study. Because coding was conducted by the course instructor, this analysis emphasizes transparency and procedural consistency rather than coder independence. To support interpretive credibility, a clearly defined rubric with explicit level definitions was applied consistently across artifacts, and coding was conducted in two rounds separated by a one-month interval to enhance intra-rater stability. Multiple data sources (reflection reports, discussion posts, peer replies, and survey data) were used to triangulate patterns across assignments. While these procedures do not substitute for inter-rater reliability, they provide a transparent and theoretically grounded basis for interpretation within a classroom-based qualitative case study.

To complement the qualitative analysis, quantitative summaries were computed from coding scores (0–3) for each dimension. One-way ANOVA was used to compare mean scores across simulation assignments. Given the ordinal nature of the coding scales and the repeated-measures structure of the data, these analyses are used to support descriptive comparison of patterns rather than confirmatory statistical inference.

4. FINDINGS

Description of Participants

Although 40 students were enrolled in the OSCM course, the analysis is based on 29 participants with complete data across all evaluated components. Since the OSCM course is part of the business core curriculum, 95% of the enrolled students were in business majors. Because of the depth and specialization of the content knowledge required for the course, no freshman students enrolled in the course. The participants' top three majors were finance (32.5%), marketing (22.5%), and applied business (17.5%), which are the common majors among business students in sophomore, junior, and senior classes.

Final Coding Schema

This research focused on comparing the cognitive engagement and depth of understanding demonstrated in reflection reports and two discussion boards. Based on the iterative coding process described in Section 3, a coding schema was developed to capture key dimensions of student learning, including *Reflective Insight and Conceptual Understanding*. The dimension *Reflective Insight* was identical for all assignments. To maintain the unique context of the AI Simulation and the 5S simulation, the focus of *Conceptual Understanding* for the AI simulation was on students' understanding and application of inventory management and negotiation principles, such as Economic Order Quantity (i.e., EOQ), inventory costs, negotiation strategies, and contractual terms, while the focus for the 5S simulation was on the key Lean philosophy and 5S principles.

Each dimension within the coding rubric had its own scale, so the same numeric level indicates different evidence depending on the dimension. Level 3 responses in *Conceptual Understanding* demonstrated integrated reasoning across multiple OSCM concepts. For example, students connected negotiation outcomes to inventory cost trade-offs and explained how changes in order quantity, pricing, or contract terms affected cost efficiency. In contrast, lower-level responses described outcomes without linking them to underlying concepts. Similarly, level 3 *Reflective Insight* responses included discussion of challenges, alternative strategies, and how these contributed to the outcome. Lower-level responses were more general, with limited reflection on the process or strategies used. In terms of *Conceptual Understanding*, although the coding rubric specifies different content domains (inventory/negotiation vs. Lean/5S) tailored to each simulation's focus, both were developed to assess the same dimension of *Conceptual Understanding*, which is students' ability to grasp and apply key OSCM principles within the context of each simulation. See Appendix C for the complete coding scale definitions (levels 0–3).

Individual Reflection Reports and Discussion Posts

Each student's reflection reports and discussions (posts and replies) for the AI simulation and discussions (posts and replies) for the 5S simulation were evaluated using a predefined coding schema. No submission received a score of 0 or 1. Therefore, only the frequencies for levels 2 and 3 are shown in Table 2. The AI simulation reflection report received the highest average score for both *Reflective Insight* (2.72) and *Conceptual Understanding* (2.79), followed by the AI simulation discussion (2.66 and 2.62, respectively). The 5S simulation discussion received the lowest scores in both categories (2.31 for each).

Coding Scale	**Reflective Insight**		
	AI Simulation Reflection	AI Simulation Discussion	5S Simulation Discussion
Level 2	8 (28%)	10 (34%)	16 (55%)
Level 3	21 (72%)	19 (62%)	11 (45%)
Total	29 (100%)	29 (100%)	29 (100%)
Avg	**2.72**	**2.66**	**2.31**
Coding Scale	**Conceptual Understanding**		
	AI Simulation Reflection	AI Simulation Discussion	5S Simulation Discussion
Level 2	6 (21%)	11 (38%)	16 (55%)
Level 3	23 (79%)	18 (66%)	11 (45%)
Total	29 (100%)	29 (100%)	29 (100%)
Avg	**2.79**	**2.62**	**2.31**

Table 2: The Effects of AI Simulation on Engagement and Understanding

Statistical comparisons were conducted using one-way ANOVA to examine differences in mean scores across simulation activities. The differences in both dimensions between the AI simulation reflection report and other assignments were statistically significant ($p < 0.1$). In addition, the differences between the AI simulation discussion and the 5S simulation discussion were significant for *Reflective Insight* ($p < 0.01$) and *Conceptual Understanding* ($p < 0.01$). A difference of approximately 0.3–0.5 points on a 0–3 scale suggests a shift from moderate to higher levels of engagement and understanding within this sample. As discussed in Section 3, given the ordinal nature of the coding scales and the repeated measures structure of the data, p values are reported as descriptive indicators of relative differences across assignments rather than as definitive evidence of statistical significance.

The post-assignment perception survey

Students' ratings about their perceptions of the value and helpfulness of two simulations were summarized using descriptive statistics, such as the percentage of responses in "Fair" category. Table 3 reports the number of students selecting each rating, with percentages in parentheses indicating the proportion relative to the total sample of 29 students. The 5S simulation discussion that is always used in the class was valued as the most interesting and helpful (93% rated it as good or excellent) compared to the two assignments based on the AI simulation (less than 80% of students rated them as good or excellent). Between the two assignments from the AI simulation, the reflection report (79.3% rated it as good or excellent), which required more effort than the discussion (72.4% rated it as good or excellent), was preferred and perceived as more valuable and useful.

	Very poor + Poor	**Fair**	**Good + Excellent**
5S Lean Discussion	1 (3.5%)	1 (3.5%)	27 (93.0%)
AI Simulation Reflection	1 (3.5%)	5 (17.2%)	23 (79.3%)
AI Simulation Discussion	1 (3.5%)	7 (24.1%)	21 (72.4%)

Table 3: Student Ratings for Assignments

5. DISCUSSION

Student Engagement and Cognitive Effort in AI Simulation

Compared to the non-AI 5S Lean Simulation, the AI-Enabled Negotiation Simulation was associated with a notably higher level of cognitive engagement and reflective thinking in the student learning process. These scores suggest that student artifacts from the AI simulation reflected more active processing of experiences, including reflection on challenges and connections to broader learning goals. For example, a student did not reveal the target cost to the supplier in order not to lose control in the negotiation, showing the active cognitive effort and strategic thinking about information asymmetry, a real negotiation tactic.

Student Conceptual Depth and Understanding in AI Simulation

The AI simulation also was associated with a deeper and higher quality level of conceptual understanding within its domain (inventory management and negotiation principles) compared to the 5S simulation within its domain (Lean/5S principles). This pattern indicates that students' work in the AI simulation more

frequently reflected integrated and comprehensive use of key OSCM concepts. For example, many students reflected that the total inventory cost was influenced by multiple factors, and thus, a low-cost deal isn't always the best deal. For example, students described how adjusting pricing, order volume, and payment structures could significantly influence total cost outcomes. Others emphasized the importance of leveraging supplier relationships to create flexibility in negotiation. These reflections on strategic decisions and holistic cost analysis illustrate how the interconnected nature of procurement negotiation and inventory management decisions was articulated in their written work.

Students' Perceptions: AI Simulation vs. 5S Simulation

Students rated the AI simulation lower than the 5S simulation in terms of "perceived usefulness and value," as reflected in the post-assignment survey. The 5S Simulation has a more mechanical nature and has been used for many years in the course and thus has well-refined instructions. In contrast, the AI simulation is a new and more complex assignment. This unfamiliarity, combined with the higher cognitive demands and less structured nature of the AI interaction, may have contributed to the lower perceived usefulness despite stronger learning outcomes.

This contrast illustrates a typical example of the "Paradox of Actual Learning" (Soderstrom & Bjork, 2015). As Soderstrom and Bjork (2015) pointed out, learners tend to rate easier, more familiar tasks as more useful, even when more challenging activities yield better understanding and insight. In other words, students' perceptions of learning effectiveness or value often diverge from their actual learning outcomes. In this study, although students perceived the 5S simulation as more useful and valuable, the AI simulation demands more sustained thinking and reflective judgment. This pattern aligns with the "desired difficulties" concept (Bjork, 1994; McDaniel & Butler, 2011), which describes how the meaningful challenges can make the initial learning harder but ultimately improve understanding and retention with deeper cognitive engagement. This divergence between perceived value and actual learning underscores the importance of interpreting student satisfaction surveys with caution, especially when evaluating innovative, cognitively demanding activities, such as the AI simulation.

From a pedagogical perspective, this suggests that instructors integrating AI-enabled simulations should provide clear guidance (e.g., step-by-step negotiation guidelines), scaffolding (e.g., sample prompts, staged reflection questions), and expectation setting to help students navigate initial difficulty. Structured reflection questions and transparent grading criteria may also help students better recognize the learning value of more cognitively demanding activities.

The Alignment with Kolb's Model

Both AI simulation and 5S simulation align well with Kolb's experiential learning theory, particularly the stages of concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984). From Appendix D, the AI simulation demonstrates deeper iterative engagement through repeated negotiation rounds, consistent with findings from students' reflections, discussion posts, and peer replies. In the concrete experience stage, students received an inventory management scenario with key variables, such as demand, pricing, and cost parameters. They were given practical preparatory materials, including what-if analyses, negotiation tips, and sample AI prompts, before entering a dynamic negotiation with an AI supplier. During the negotiation process, students interacted with the AI supplier for several rounds and experienced trial and error, strategic adjustment, and decision-making under constraints, all of which are core aspects of experiential learning.

Students engaged in the reflective observation stage through each round of negotiation by analyzing both their achievements and setbacks in the simulation. Many students referenced moments of challenge (e.g., rejected offers), which led them to rethink their original strategies. These reflections often progressed into abstract conceptualization, where students formulated general principles about negotiation and inventory cost analysis (e.g., the trade-offs between multiple cost drivers). In the final stage, active experimentation, students applied these insights in subsequent negotiation rounds, adjusting their counter offers to reflect a more holistic and strategic perspective (e.g., requesting a credit reimbursement to offset the high price or offering longer contract terms in exchange for a lower price).

Overall, the AI simulation was designed to align with all four stages of Kolb's (1984) model, and student reflections and discussion artifacts suggest engagement across these stages. Importantly, the simulation's iterative design allows students to cycle through Kolb's model

multiple times. Since the cost target cannot be reached in a single negotiation round, each new contract outcome becomes part of the next concrete experience, initiating a new round of learning. This spiral learning process deepens student engagement and reinforces the connection between all four stages of Kolb's model, which is less evident in 5S simulation. As a result, the AI simulation aligns with Kolb's (1984) framework and illustrates how structured iteration may extend experiential learning cycles within an applied OSCM context.

6. CONCLUSION AND FUTURE WORK

The AI Simulation was associated with deeper conceptual understanding and more reflective insights than the 5S Lean Simulation, despite the AI-enabled assignments receiving lower student ratings for perceived value and usefulness. The findings align with prior study (Poo & Qi, 2023) and Kolb's experiential learning cycle (Kolb, 1984), illustrating how AI-enabled activities may be associated with higher levels of cognitive effort and critical thinking within a single-course implementation. This highlights the pedagogical value of designing "desired difficulties" in experiential learning to challenge students meaningfully (Bjork, 1994; McDaniel & Butler, 2011). The study offers insights into how Kolb's experiential learning cycle may operate in a more iterative, spiral-like process through multiple negotiation rounds with iterative reflection (Appendix E). In addition, this research advances OSCM teaching practices by demonstrating how AI can be responsibly integrated to build both technical (e.g., order quantity calculation) and durable human skills (e.g., negotiation), preparing students for complex OSCM roles that demand agility, data-driven decision-making, and negotiation competence.

Practically, the gap between AI tools' availability and the workforce's ability to use them effectively remains a critical challenge for businesses. Patterns observed in student engagement, reflective thinking, and conceptual understanding suggest that educational programs integrating AI literacy and experiential learning can help address this skills gap. By preparing future supply chain professionals with practical experience in AI-enabled decision-making, organizations can build a workforce better equipped to leverage AI capabilities for strategic advantage. Practitioners can apply these insights by collaborating with educational partners to design hands-on, AI-enabled simulations that encourage learners to engage deeply, reflect critically, and develop problem-solving strategies relevant to fast-evolving supply chain environments where agility and data-driven strategies are increasingly important.

While this study was conducted as an exploration of a single course implementation, the findings provide a foundation for the future iterative refinement of the AI Simulation and the development of more structured evaluation tools. Future research may extend this work through larger samples, independent coding with a second coder, and longitudinal analysis, to improve the credibility and robustness of findings over time. These adjustments would enable deeper investigation of the pedagogical impact of AI integration on student learning outcomes in OSCM education.

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Appendix A

Distribution of Respondents and Non-Respondents by Student Majors and Class Standing

	Class Demographics N (%)	**Study Participants N (%)**	**Study Nonparticipants N (%)**
Major			
Finance	13 (32.5%)	13 (44.8%)	0 (0%)
Marketing	9 (22.5%)	8 (27.6%)	1 (9.1%)
Applied Business	7 (17.5%)	3 (10.3%)	4 (36.4%)
Accounting	3 (7.5%)	3 (10.3%)	0 (0%)
Entrepreneurship	2 (5%)	0 (0%)	2 (18.2%)
Bio Marketing	1 (2.5%)	1 (3.4%)	0 (0%)
Business Analytics	1 (2.5%)	0 (0%)	1 (9.1%)
Sports Management	1 (2.5%)	0 (0%)	1 (9.1%)
Business Undecided	1 (2.5%)	0 (0%)	1 (9.1%)
Non-Business Major	2 (5%)	1 (3.4%)	1 (9.1%)
Total	**40 (100%)**	**29 (100%)**	**11 (100%)**
Class Standing			
Sophomore	24 (60%)	21 (72%)	3 (27.3%)
Junior	12 (30%)	7 (24.1%)	5 (45.5%)
Senior	4 (10%)	1 (3.4%)	3 (27.3%)
Total	40 (100%)	29 (100%)	11 (100%)

Appendix B:

Post-Assignment Survey Questions

Please rate how much you liked the **Discussion #3: Simulation results discussion (procurement negotiation simulation)** overall, considering how interesting it was and how much it helped you understand the operations and supply chain management.

1. Very poor
2. Poor
3. Fair
4. Good
5. Excellent

Please rate how much you liked the **Discussion #4: 5S game and lean** overall, considering how interesting it was and how much it helped you understand the operations and supply chain management.

1. Very poor
2. Poor
3. Fair
4. Good
5. Excellent

Appendix C

Coding Schema for Conceptual Understanding and Reflective Insight

Theme	Depth Levels			
Conceptual Understanding (AI-Enabled Negotiation Simulation) Demonstrates understanding and varying levels of application of key inventory management and negotiation principles.	**0 = Absent** No relevant concepts are identified or applied.	**1 = Surface-level** Provides a basic or incomplete response (e.g., mentions cost analysis, negotiation approach, or contract terms) without explanation or clear reasoning.	**2 = Applied** Demonstrates a clear understanding and partial application of inventory management and negotiation principles (e.g., explains cost analysis or negotiation approach with some reasoning).	**3 = Integrated and insightful** Demonstrates a comprehensive and well-reasoned application of multiple concepts (e.g., full cost analysis, strategic negotiation with clear rationale, and justified contract terms with impact).
Conceptual Understanding (Non-AI 5S Lean Simulation) Demonstrates understanding and varying levels of application of key lean philosophy and 5S principles.	**0 = Absent** No relevant Lean or 5S concepts are identified or applied.	**1 = Surface-level** Provides an incomplete or basic response with limited explanation of Lean philosophy or 5S principles.	**2 = Applied** Demonstrates a clear understanding and partial application of Lean philosophy and 5S principles (e.g., explains how specific steps improve organization or efficiency with some reasoning).	**3 = Integrated and insightful** Demonstrates a comprehensive and well-reasoned application of multiple Lean and 5S principles (e.g., integrates several steps to explain process improvements with clear rationale and impact).
Reflective Insight (AI-Enabled Negotiation Simulation and non-AI 5S Lean Simulation) Reflects on learning, challenges, and implications for professional practice	**0 = Absent** No meaningful reflection on the experience is provided.	**1 = General** Provides a vague reflection on the experience, with limited detail about what was learned and little discussion of challenges.	**2 = Specific** Provides a specific reflection on the experience, describing particular challenges or strategies and offering some explanation of what was learned.	**3 = Deep and personal** Provides a deep and personal reflection on the experience, including detailed discussion of challenges and strategies, and clear insights into learning, growth, or future application.

Appendix D

Alignment of Simulations with Kolb's Experiential Learning Cycle

Kolb's Stage	AI-Enabled Negotiation Simulation	5S Lean Simulation
Concrete Experience	Work with inventory management scenarios (demand, pricing, cost variables); engage in multi-round negotiations with an AI supplier using preparatory tools (what-if analyses, negotiation tips, AI prompts).	Perform sorting and error-finding tasks in interactive 5S game scenarios; experience incremental task improvements.
Reflective Observation	After each negotiation round, analyze outcomes, setbacks, and rejected offers; reflect in reports and discussion posts.	Reflect on efficiency gains and mistakes; share brief insights in discussion posts.
Abstract Conceptualization	Formulate general principles about negotiation, trade-offs, and inventory cost drivers; connect to OSCM theory.	Generalize Lean/5S principles; connect task outcomes to workplace organization concepts.
Active Experimentation	Apply revised strategies in subsequent negotiation rounds (e.g., adjust counteroffers, modify contract terms); cycle iteratively through Kolb's stages.	Apply 5S principles in later scenarios or envision applications to daily/work contexts; typically completes a single cycle.

Appendix E

Theoretical Contribution

