AI-Assisted Negotiation Training: A Quasi-Experimental Examination of Buyers' and Sellers' Perceived Negotiation Performance in a Used-Car Sales Simulation

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ABSTRACT

Background: Evidence on artificial intelligence (AI) as a preparatory learning aid for novice human negotiators remains limited in consumer negotiation simulations. Existing work emphasizes automated agents rather than students preparing to negotiate. Against this backdrop, the present study examined changes in students' perceived negotiation performance, differences in those changes between buyer and seller roles, and the purposes for which students used AI during a simulated used-car sale. The outcome was perceived performance, not economic results.

Methodology: A single-group, repeated-measures quasi-experiment involved 74 undergraduate business students enrolled in a negotiation course at a university in Bangkok, Thailand. Thirty-seven students served as buyers and 37 as sellers. Participants completed two negotiations outside regular class hours within a 24–48-hour period, retaining their assigned roles and using the same scenario. The first round was conducted without AI assistance. Before the second round, students spent approximately five minutes preparing with generative AI tools of their choice for information analysis, strategy planning, role-play, or feedback. Each negotiation lasted approximately five to seven minutes. Perceived negotiation performance was assessed using five-item self-report scales in each condition. Paired-samples t-tests and a mixed-design analysis of variance (ANOVA) examined differences between conditions and across roles. Reported purposes of AI use were summarized descriptively.

Results: Students reported higher perceived negotiation performance after AI-assisted preparation (M = 4.45, *SD* = 0.42) than after the preceding non-AI round (M = 3.78, SD = 0.58). The mean difference was 0.67 points, $t(73) = -9.23$, $p < .001$, with a large standardized difference ($|d| = 1.07$). The mixed-design ANOVA identified a significant condition effect, $F(1, 72) = 83.97$, $p < .001$, partial $\eta^2 = .54$, but no significant condition-by-role interaction. Buyers' mean scores increased by 0.68 points and sellers' by 0.66 points. Information analysis was the most frequently reported purpose of AI use (91.9%), followed by

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strategy planning (60.8%), role-play practice (51.4%), and feedback (40.5%). These descriptive patterns do not establish the effectiveness of individual AI functions.

Discussions: The findings suggest that AI may provide useful analytical and strategic support during experiential negotiation preparation. Similar patterns of change across buyer and seller roles indicate that the observed increase in perceived performance was not statistically distinguishable between the two groups; the groups do not demonstrate equal bargaining power or equivalent economic outcomes. Students' greater use of information analysis and planning than of interactive practice also points to a possible area for instructional development. However, the fixed order of conditions and repetition of the same scenario mean that practice and familiarity may have contributed to the higher ratings in the second round.

Conclusions: AI-assisted preparation was associated with substantially higher self-reported negotiation performance in this educational simulation. The findings reflect students' perceptions, not independently assessed negotiation quality, agreed prices, fairness, or information asymmetry. Accordingly, they should not be interpreted as a causal estimate of AI's contribution to objective negotiation performance. Future studies should counterbalance condition order, include behavioral measures, and recruit more diverse participants.

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Introduction

Artificial intelligence (AI) has rapidly become an important tool for supporting information processing, decision-making, and human–computer collaboration. In negotiation, AI can assist with data gathering, preparation, option generation, and evaluation of proposed terms, while recent generative AI systems have expanded the range of support available to human negotiators (Cummins & Jensen, 2024; Luo et al., 2024). Despite these developments, the role of AI in negotiation remains less extensively examined than its broader applications in decision support and higher education. Negotiation itself is a demanding activity in business and everyday life, often requiring individuals to interpret incomplete information, evaluate alternatives, manage interpersonal dynamics, and make decisions under uncertainty.

Negotiation constitutes a fundamental element of human interaction that influences outcomes across personal, professional, and societal settings. Its effectiveness depends on both analytical reasoning and interpersonal sensitivity. Human negotiators may face limitations in information processing, planning, emotional regulation, and strategic preparation, creating opportunities for appropriately designed AI tools to provide complementary support (Cummins

& Jensen, 2024; Luo et al., 2024). Consumer-oriented negotiation provides a particularly relevant setting for examining such support because participants often need to evaluate product information, estimate value, establish bargaining positions, and develop strategies with limited preparation. Used-car sales provide a familiar and accessible context for such experiential practice. AI can assist these preparatory processes through data analysis, strategic suggestions, and interactive support. Research on AI and negotiation similarly suggests that AI can contribute to negotiation preparation and decision support, although its role varies substantially according to whether AI acts as an assistant, semi-autonomous system, or autonomous negotiating agent (Falcão Filho, 2024; Luo et al., 2024).

Although scholarship on AI and negotiation is expanding, the existing literature remains fragmented across several distinct streams. Research on automated negotiation has largely examined computational agents, algorithmic strategies, and negotiated outcomes, while emerging work on generative AI has considered how AI can assist human negotiators with planning and decision support (Cummins & Jensen, 2024; Falcão Filho, 2024). At the same time, research on human–AI collaboration in higher education has highlighted the potential for AI to support learning when it complements rather than replaces human cognitive processes (Atchley et al., 2024; Kong et al., 2025). What remains comparatively underexamined is the intersection of these two streams: the pedagogical use of AI by novice human negotiators during experiential negotiation training. In particular, limited empirical evidence shows how students use AI during preparation, whether perceived performance changes following AI-assisted preparation, and whether such patterns differ across buyer and seller roles in consumer-oriented negotiation simulations. This pedagogical gap constitutes the central focus of the present study.

AI's potential contribution to negotiation training extends beyond automation. Generative AI can support preparatory activities by helping users organize information, explore alternatives, formulate strategies, and reflect on possible approaches before interacting with another party. Cummins and Jensen (2024), for example, reported that the use of ChatGPT in negotiation was associated with more structured preparation and differences in how participants approached the negotiation process. Automated negotiation research likewise demonstrates the capacity of computational systems to process multiple issues and adapt bargaining strategies (Chen et al., 2025; Luo et al., 2024). However, evidence derived from autonomous negotiation systems should not be treated as direct evidence of learning effects among students using AI as a preparatory tool. The distinction is important because the present study examines human negotiators who retain responsibility for the negotiation itself, with AI used during preparation rather than as the negotiating party.

Studies involving consumer-oriented applications provide additional context for this distinction. Liu and Zheng (2020) developed a negotiation-assistance system incorporating machine-learning-based price prediction, illustrating how computational support can inform negotiation-related decisions. Similarly, Selvakanmani et al. (2024) demonstrated the use of AI for predicting vehicle resale values. These studies show the relevance of AI-based analytical support to price-related consumer decisions, but they do not establish that AI necessarily eliminates information disparities, improves fairness between negotiating parties, or produces superior negotiation outcomes in student simulations. Accordingly, the used-car setting in the present study is treated as a realistic and relatable context for negotiation training rather than as a direct test of the economic mechanism of information asymmetry.

The potential value of AI must also be considered alongside its limitations. AI systems do not reproduce the full range of socio-emotional and relational capabilities involved in human interaction. Research on human–AI collaboration emphasizes the continuing importance of socio-emotional attributes and human judgment when interactions require sensitivity to contextual and interpersonal cues (Kolomaznik et al., 2024). Ethical scholarship further identifies transparency, fairness, responsibility, and human oversight as recurring concerns in the development and application of AI systems (Jobin et al., 2019). These considerations are particularly relevant to negotiation, where relational judgment, ethical evaluation, and interpretation of another party's intentions cannot be reduced to analytical processing alone. Consequently, AI is more appropriately positioned as a complement to human negotiation than as a substitute for human judgment (Falcão Filho, 2024).

From an educational perspective, this complementary role is consistent with emerging approaches to human–AI collaboration in higher education. Atchley et al. (2024) argue that AI-supported tools can facilitate learning when incorporated in ways that preserve learners' active cognitive engagement, while Kong et al. (2025) demonstrate that the configuration of human–AI collaboration influences learning processes within hybrid intelligence environments. These perspectives provide a stronger pedagogical basis for examining AI-assisted negotiation training than approaches concerned primarily with autonomous bargaining performance. Negotiation simulations require learners to act, evaluate their experience, reconsider their strategies, and apply revised approaches. AI-assisted preparation may therefore function as a cognitive and reflective scaffold within this experiential process by helping learners organize information and formulate strategies while leaving the interpersonal negotiation itself under human control.

Evidence from organizational negotiation research also illustrates why the distinction between AI as negotiator and AI as learning support must be maintained. Herold et al. (2025), for example, experimentally examined AI-based chatbots in buyer–supplier negotiations and demonstrated that different chatbot negotiation approaches produced different economic, psychological, and relational outcomes. Such findings provide useful evidence about AI participation in negotiation but address a different question from the pedagogical issue examined here. The present study does not evaluate an autonomous AI negotiator, objective economic outcomes, information asymmetry, or bargaining fairness. Instead, it examines students' perceived negotiation performance following AI-assisted preparation and the ways in which students report using AI during that preparation.

Taken together, the literature indicates that AI has meaningful potential in negotiation but also reveals a specific unresolved educational question. Existing studies demonstrate AI capabilities in automated bargaining, negotiation assistance, price-related analysis, and human–AI collaboration, yet comparatively little empirical work examines AI as a preparatory learning aid for novice negotiators participating in experiential simulations. The strongest contribution of the present study therefore lies not in testing whether AI removes information asymmetry or makes negotiation objectively fairer, but in examining how AI-assisted preparation is associated with students' perceived negotiation performance and how learners employ AI within a structured negotiation-training activity. The use of a used-car sales simulation provides an accessible consumer context in which these pedagogical processes can be examined.

Accordingly, this study examines changes in perceived negotiation performance rather than objective negotiation performance. It also compares patterns of change between buyer and seller roles without assuming that similar changes represent equivalent bargaining power,

reduced information asymmetry, or objectively fairer outcomes. In addition, the study investigates the purposes for which students use AI during negotiation preparation and evaluates the magnitude of the observed change to assess its practical relevance for negotiation education. The study is guided by four research objectives:

1) To examine changes in students' perceived negotiation performance following AI-assisted preparation compared with the preceding non-AI negotiation condition in a used-car sales simulation.

2) To compare changes in perceived negotiation performance between buyer and seller roles and determine whether the pattern of change differs by negotiation role.

3) To evaluate how AI is used during negotiation preparation—including information analysis, strategy planning, role-play, and feedback—and identify which purposes students prioritize most.

4) To assess the magnitude of the observed change in perceived negotiation performance following AI-assisted preparation and its practical significance for negotiation teaching.

By addressing these objectives, the study contributes to negotiation education and human–AI learning research by examining AI as a pedagogical support tool within an experiential negotiation activity. Its contribution is deliberately bounded to students' perceived performance and reported AI-use patterns; it does not claim to demonstrate improvements in objective negotiation outcomes, reductions in information asymmetry, or increases in bargaining fairness. This more circumscribed positioning provides a clearer basis for evaluating the educational relevance of AI-assisted preparation while preserving the distinction between AI-supported learning and autonomous AI negotiation.

Review of Literature

The integration of artificial intelligence (AI) into sectors such as finance, healthcare, and transportation is well-established, but its application in negotiation processes is still developing. Negotiations often involve repeated exchanges, high stakes, and uncertainty, which can create particular challenges for less experienced negotiators. AI may support these situations by providing structured decision support, predictive modeling, and interactive learning environments. Building on these characteristics of negotiation, recent work in learning sciences and human–AI collaboration highlights that AI should be viewed not just as an automation tool but as a facilitator that supports learners' cognitive and metacognitive regulation. Evidence from higher education research collectively suggests that the educational value of AI depends on how it complements learners' cognitive processes and how human and AI contributions are coordinated within the learning environment (Atchley et al., 2024; Kong et al., 2025).

From an educational-theory perspective, Kolb's experiential learning cycle, encompassing experience, reflection, conceptualization, and experimentation, provides a theoretical framework relevant to simulation-based teaching (Kolb, 1984). Lee and Kumar (2023) illustrate how experiential learning theory can inform curriculum design and reflective learning practices. When AI is integrated into this cycle to provide timely analytics and feedback, it aligns with current research on generative AI in education, which highlights potential contributions to learning design, regulation of learning, feedback, and assessment while also emphasizing ethical and pedagogical considerations (Giannakos et al., 2025). These studies suggest that AI-supported learning is most appropriately understood as a complement to learners' active

participation and reflection rather than as a replacement for those processes (Atchley et al., 2024; Giannakos et al., 2025; Kong et al., 2025; Lee & Kumar, 2023).

Collectively, these studies provide a theoretical basis for positioning AI-assisted negotiation training as a pedagogical support approach informed by experiential learning and human–AI collaboration, with potential to support structured preparation, reflection, and strategic reasoning (Al-Zahrani & Alasmari, 2024; Atchley et al., 2024; Giannakos et al., 2025; Kong et al., 2025; Lee & Kumar, 2023).

Despite rich developments in both AI negotiation agents and AI-supported learning systems, the literature reviewed above points to a more focused pedagogical gap. Research on AI-assisted negotiation has predominantly emphasized computational performance, automated agents, or algorithmic tactics, whereas comparatively little empirical research has examined how AI supports novice human negotiators during experiential learning and preparation. Consumer-focused simulations, including used-car sales, also remain relatively underexamined as contexts for AI-assisted negotiation training. Accordingly, the central contribution of the present study is to examine how AI-assisted preparation is associated with students' perceived negotiation performance, whether patterns of change differ between buyer and seller roles, and how students use AI during preparation in a consumer-focused experiential simulation. The used-car setting is therefore treated as a realistic training context rather than as a direct test of information asymmetry, bargaining power, or market fairness.

Liu and Zheng (2020) introduced an intelligent negotiation assistant that used decision-tree modeling to forecast car prices and provide advice to buyers. Similarly, Selvakanmani et al. (2024) developed AI-based models for predicting vehicle resale values, demonstrating the relevance of AI-supported analytical information to buying and selling decisions in the used-car context. Together, these studies provide contextual evidence for the use of AI in analytical preparation, although they do not directly establish improvements in students' negotiation performance. These studies provide relevant background for *H1, which posits that students will report significantly higher perceived negotiation performance following AI-assisted preparation than following the non-AI negotiation condition*.

Research on automated negotiation further suggests that AI systems can support negotiation-related decision processes across different bargaining situations, although findings from automated agents should not be interpreted as evidence of equal bargaining power or fairness among student negotiators. Luo et al. (2024) provide a comprehensive synthesis of human factors, learning mechanisms, and adaptability in automated bargaining systems. Similarly, Sizon et al. (2020) examined the application of artificial intelligence models to negotiation. These studies demonstrate the broader applicability of AI to negotiation processes but do not establish that buyers and sellers in the present study receive objectively equal or fair outcomes. They instead provide a basis for examining whether the pattern of change in perceived negotiation performance differs according to negotiation role. Thus, *H2 predicts that the change in perceived negotiation performance from the non-AI condition to the AI-assisted condition will not differ significantly between buyers and sellers*.

Recent studies highlight how AI can support negotiation by combining information processing, automation, and adaptive strategies. Li (2024) discusses the potential of AI negotiation agents to support data collection, pattern analysis, outcome prediction, and adaptive strategy development, while Luo et al. (2024) synthesize developments in automated negotiation and machine-learning-based adaptation. Related empirical work demonstrates the

application of reinforcement learning to multi-issue negotiation (Chen et al., 2025) and the development of adaptive negotiation models incorporating preference and emotional information (Wu & Sun, 2025). Kobiella et al. (2025) further extend this literature by examining AI in a moderation role rather than as a direct negotiating party. Considered together, these studies show that AI can materially influence negotiation-related processes across different technological configurations, although their outcomes are not directly equivalent to the perceived performance measured in the present educational simulation. Accordingly, *H3 predicts that the observed change in perceived negotiation performance following AI-assisted preparation will demonstrate a practically meaningful effect size*.

Finally, research also highlights significant limitations that define the scope of AI's use in negotiation training. Cummins and Jensen (2024) discuss both the opportunities and limitations associated with AI-supported negotiation. Herold et al. (2025) experimentally demonstrated that different AI-based negotiation approaches can produce different economic, psychological, and relational outcomes in buyer–supplier negotiations, indicating that the consequences of AI support depend partly on how the technology is configured and used. Complementary findings by Kolomaznik et al. (2024) emphasize the importance of socio-emotional attributes in human–AI collaboration, while Falcão Filho (2024) similarly emphasizes a collaborative relationship between human negotiators and AI rather than complete substitution. Collectively, these perspectives support the use of AI as a complement to human negotiation, providing analytical and preparatory support while leaving interpersonal judgment, ethical interpretation, and relational management with the human negotiator. This distinction is particularly relevant to skill-based training such as the used-car sales simulation examined in the present study.

Research Methods

This study outlines the methodological framework employed to examine the impact of AI on negotiation performance. A quasi-experimental design was implemented to allow for comparisons between traditional negotiation practice and AI-supported conditions. The procedures, sampling approach, and ethical considerations are presented below to ensure clarity and replicability. To strengthen methodological transparency, this section also addresses potential threats to internal validity, justifies the sampling approach, and provides explicit details about the AI tools used to support replicability and future comparative studies

Research Design

The study employed a single-group, repeated-measures quasi-experimental design in which the same participants completed two sequential negotiation conditions. Quasi-experimental designs are particularly useful in applied educational settings where full randomization may not be feasible, although alternative explanations for observed changes must be considered when interpreting the results (Shadish et al., 2002). In Round 1, students conducted the negotiation without AI support. They subsequently used AI during the preparation stage before completing Round 2 using the same negotiation scenario and retaining the same buyer or seller role.

Both rounds were completed outside regular class hours within a fixed 24-48-hour period. This arrangement allowed students to engage with the activity independently while maintaining a common timeframe, scenario, and set of instructions across participants. The

within-subject design also allowed each participant's perceived performance in the two conditions to be compared directly.

The order of the two conditions was fixed rather than counterbalanced: all participants completed the non-AI round first and the AI-assisted round second. Because the same scenario was used in both rounds, the design cannot fully separate the contribution of AI-assisted preparation from practice, scenario familiarity, or other order-related effects. The observed differences are therefore interpreted as changes following AI-assisted preparation rather than as an isolated causal effect of AI.

Participants

The participants were undergraduate business students enrolled in a negotiation course at Rajamangala University of Technology Phra Nakhon. A total of 74 students participated in the study, evenly divided into buyer and seller roles for the negotiation simulations. Each participant experienced both the non-AI and AI-assisted conditions, allowing for within-subject comparisons. The instructor assigned the buyer and seller roles to each student pair before Round 1. The role assignment was not randomized, and participants retained the same roles in Round 2 to maintain role consistency across the two conditions. Participation was voluntary, and informed consent was obtained from all students before data collection.

Unlike typical classroom-based quasi-experiments, students in this study completed the negotiation activity outside regular class hours as part of an assigned experiential learning task. This approach was intentionally chosen to increase ecological realism, allowing participants to interact with AI tools in a flexible, self-directed environment that reflects how individuals naturally use AI in real negotiation preparation. Because all students in the course were required to complete the same assignment, a census sampling strategy was still applied, but without the constraints of in-class timing or instructor supervision.

Because the researcher was also the course instructor, the distinction between completing the course activity and participating in the research was explicitly communicated to students during the informed-consent process. The instructor explained that completion of the negotiation activity was a course requirement, whereas consent to use students' data for research purposes was entirely voluntary. Students were informed that agreeing or declining to participate would have no effect on their grades, course standing, or relationship with the instructor, and that they could withdraw their research participation without academic penalty. Confidentiality of the research data was also explained before consent was obtained. These safeguards were used to reduce the potential for undue influence arising from the instructor–student relationship (Tulyakul & Meepring, 2020).

Conducting the activity outside scheduled class periods also minimized several threats to internal validity. Maturation and history effects were reduced by requiring students to complete both negotiation rounds within a defined short time window (approximately 24–48 hours), preventing long gaps that could have introduced uncontrolled influences. Additionally, because students completed the tasks independently and submitted video evidence of both rounds, risks of peer influence or collaborative bias were substantially reduced. The fixed assignment of buyer–seller roles maintained identity consistency, while the within-subject design controlled for individual skill differences.

Instruments

Two separate instruments were created to measure perceived negotiation performance in each condition (Non-AI and AI-assisted). Each instrument included five items rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), following established guidelines for scale construction and attitudinal measurement (DeVellis & Thorpe, 2022). The non-AI scale showed acceptable reliability (Cronbach's α = .717). Similarly, the AI-assisted scale demonstrated acceptable reliability (Cronbach's α = .709), meeting the commonly used .70 benchmark for acceptable internal consistency (Nunnally & Bernstein, 1994). The measurement framework was developed to capture students' self-reported perceptions of their negotiation performance, drawing conceptually on previous research concerning subjective negotiation outcomes and negotiation processes. Example items included "I was satisfied with the negotiation outcome" and "I can develop better negotiation strategies," informed conceptually by Thompson et al. (2010) and Curhan et al. (2010).

Because the instruments relied on students' self-reports, the measured outcome represents perceived negotiation performance rather than objective negotiation performance. The instruments did not assess behavioral or economic outcomes such as the final agreed price, number of concessions, or value created during the negotiation.

Additional materials used in the activity included:

• Negotiation scenario documents and PowerPoint slides outlining buyer–seller contexts.

• Negotiation planning worksheet for pre-negotiation strategy formulation.

• AI bot tools, including generative AI systems such as ChatGPT and other AI platforms selected by students, for post–Round 1 preparation and reflective analysis.

• The AI Bot Usage Log Form, used to document the AI platform selected, the purpose of use, prompts entered, AI responses, and how the generated information or strategy would be applied in Round 2 (see Appendix). Students were allocated approximately five minutes for AI-assisted preparation.

• Comparative reflection and evaluation forms for analyzing perceived performance differences between the non-AI and AI-assisted conditions.

Procedures

The study employed a quasi-experimental pre–post design involving two rounds of negotiation. All participants completed the conditions in the same sequence, beginning with the non-AI condition and followed by the AI-assisted condition. The process comprised six stages (see Table 1), as outlined below:

1. Pre-activity stage – Students reviewed the scenario and their assigned roles (buyer/seller) using the provided documents to ensure clarity and readiness.

2. Round 1 (Negotiation without AI) – Students took part in a role-play negotiation without AI help. Each pair conducted a simulated second-hand car sales negotiation, lasting 5–7 minutes, which was video-recorded.

3. Preparation after Round 1 – Students used GPT or other generative AI tools for approximately five minutes to analyze their Round 1 experience, develop negotiation strategies, and practice with AI. Students documented their AI use in the AI Bot Usage Log Form, including the AI platform used, purpose of use, prompts, AI responses, and intended application of the information or strategies in Round 2 (see Appendix).

4. Round 2 (Negotiation with AI-assisted preparation) – Students repeated the negotiation using the same scenario and retaining the same buyer or seller roles, now using AI-generated information and strategies. The simulation lasted 5–7 minutes and was also video-recorded (see Appendix).

5. Post-activity stage – Students reviewed and reflected on the differences between Rounds 1 and 2 using comparative worksheets and evaluation forms.

6. Final submission – Students compiled both recorded video links (uploaded to YouTube) and all completed appendices into a PDF for submission.

In contrast to controlled in-class experiments, all six stages were completed *outside of regular class hours* as part of an assigned experiential learning project. Students were given a fixed time window (24–48 hours) to complete both negotiation rounds and the AI-assisted preparation, ensuring consistency while still allowing naturalistic interaction with AI tools. This approach was intentionally chosen to reflect how individuals would realistically prepare for real-world negotiations using online platforms and AI support tools.

To reduce threats to internal validity, clear written instructions, standardized documents, and identical scenario packets were provided to all participants. Students were explicitly instructed not to collaborate with peers. Video recordings of both negotiation rounds provided a means of verifying completion of the required simulations and their sequence. These procedural controls improved consistency across participants but did not eliminate possible practice, familiarity, or order effects arising from completing the same scenario first without AI and subsequently following AI-assisted preparation.

Because the order of the two conditions was not counterbalanced, changes in perceived negotiation performance between Rounds 1 and 2 cannot be attributed solely to AI-assisted preparation. Repetition of the same scenario and prior experience from Round 1 may also have contributed to the observed change. This design feature was therefore considered when interpreting the findings.

Although students completed the activity independently, the structured timing, uniform materials, and within-subject design provided a consistent procedural framework for comparing perceived negotiation performance across the two rounds while retaining the out-of-class experiential setting.

Table 1

Procedure for the Used-Car Sales Negotiation Training Activity (Non-AI vs. AI Conditions)

Step	Description	Objective	Tools/ Materials	Video Recording
Pre-activity stage	Students in each role (buyer or seller) carefully study the details of the scenario and their assigned role.	To ensure understanding and preparation.	Activity documents, PowerPoint slides, and negotiation planning worksheet	☒

Table 1

(Cont.)

Step	Description	Objective	Tools/ Materials	Video Recording
Round 1 (Negotiation without AI)	Students conduct role-play negotiations (buying and selling) without any AI support.	To develop skills in understanding distributive negotiation without AI assistance	Only information self-searched by students from the Internet	☑Video recording (simulation of used-car sales negotiation practice lasting approximately 5–7 minutes)
Preparation after Round 1	Students use GPT or other generative AI tools for approximately five minutes to (a) analyze their Round 1 experience, (b) develop negotiation strategies, and (c) practice with AI. AI use is documented in the AI Bot Usage Log Form.	To develop skills and prepare new strategies	Generative AI tools and AI Bot Usage Log Form (see Appendix)	☒
Round 2 (Negotiation with AI-assisted preparation)	Students conduct a second negotiation using the same scenario and retaining the same roles, this time applying information and strategies derived from AI-assisted preparation.	To examine changes in perceived negotiation performance following AI-assisted preparation.	Information and strategy generated from AI	☑Video recording (simulation of used-car sales negotiation practice lasting approximately 5–7 minutes)

Table 1
(Cont.)

Step	Description	Objective	Tools/ Materials	Video Recording
Post-activity stage	Students analyze differences between Round 1 and Round 2 by writing a reflective summary.	To reflect on learning experiences across the two negotiation rounds.	Negotiation scenario comparative worksheet, evaluation form comparing Round 1 and Round 2	☒
Final submission stage	Students compile all documents and upload videos.	To submit the outcomes of the used-car sales negotiation training activity	Submission checklist	☒

Source: Author's Development

Data Analysis

Quantitative data were analyzed using SPSS. The following analyses were conducted:

1. Reliability analysis of perceived negotiation performance scales under both conditions with Cronbach's alpha.

2. Paired-samples t-test comparing perceived negotiation performance between the Non-AI and AI-assisted conditions.

3. A mixed-design ANOVA was employed to assess whether changes in perceived negotiation performance differed between buyers and sellers, with condition (Non-AI vs. AI-assisted) as the within-subjects factor and role (buyer vs. seller) as the between-subjects factor. Effect sizes (Cohen's d, Hedges' g, and partial η^2) were calculated and reported alongside p-values to indicate the magnitude of the observed effects.

To ensure robust statistical results, the dataset was checked for missing values and outliers before analysis. No missing data were found, and all scores fell within ±3 standard deviations of the mean. Assumptions of normality (Shapiro–Wilk) and homogeneity of variance (Levene's test) were met. The final sample comprised 74 participants. Effect sizes were reported alongside the significance tests to indicate the magnitude of the observed differences. Cohen's d was interpreted using the conventional benchmarks of .20, .50, and .80 for small, medium, and large effects, respectively (Cohen, 1992), while partial η^2 was reported as an additional measure of effect magnitude.

Because data were collected from out-of-class, self-directed negotiation activities, additional steps were taken to ensure analytic reliability. All video submissions were time-stamped and cross-checked against submission logs to confirm that Round 1 and Round 2 were completed within the assigned 24–48-hour window, reducing the risk of temporal bias or performance drift. Any incomplete or suspicious submissions were pre-screened before inclusion.

The paired-samples t-test was supplemented with a Wilcoxon signed-rank test to assess robustness to potential non-normality arising from self-directed performance variation. Both tests yielded convergent results, strengthening confidence in the outcome patterns.

For the mixed ANOVA, assumption checks included tests of normality and homogeneity of variances. Because the within-subjects factor had only two levels, sphericity was inherently satisfied. Partial η^2 was reported to provide a clear indication of effect magnitude, which is commonly used in educational intervention studies.

Qualitative reflections were reviewed using a simple inductive approach to identify common themes related to students' AI use. Although not analyzed with formal coding procedures, these reflections provided contextualized insights that complemented the quantitative results, especially regarding how students relied on AI for information analysis and strategic planning.

Given the activity's out-of-class nature, all analytic steps were documented to enhance transparency and enable replication. This includes standardized instructions, consistent timing windows for both negotiation rounds, and criteria for reviewing student submissions. These measures ensured consistency across participants and supported the reproducibility of the AI-assisted negotiation training design.

Findings

This section presents the study's findings, beginning with a description of participant characteristics, followed by analyses of AI-use purposes, perceived negotiation performance comparisons, and relevant statistical tests. The results are structured to address the study's research objectives and hypotheses directly. Before conducting the hypothesis tests, assumptions of normality, homogeneity of variance, and the absence of outliers were examined and met acceptable criteria, supporting the validity of the subsequent paired-samples t-test and mixed-design ANOVA analyses.

Table 2

Distribution of Participants by Gender (n = 74)

Gender	Frequency	Percent
Male	16	21.6%
Female	58	78.4%
Total	74	100%

Table 2 shows the distribution of participants by gender. Out of 74 students, 16 (21.6%) were male, and 58 (78.4%) were female. This indicates that the sample was predominantly female, comprising more than three-quarters of the participants. Gender was reported as a demographic characteristic but was not specified as an explanatory variable in the original research design; consequently, no inferential comparison of perceived negotiation performance by gender was conducted. The gender imbalance is considered when discussing the generalizability of the findings.

Table 3

Purpose of Using AI for both Buyer and Seller (n = 74)

Objectives	Yes (%)	No (%)	Total
Objective 1 – Plan negotiation strategies	45 (60.8%)	29 (39.2%)	74
Objective 2 – Analyze car-related information	68 (91.9%)	6 (8.1%)	74
Objective 3 – Receive feedback from AI after negotiation	30 (40.5%)	44 (59.5%)	74
Objective 4 – Practice negotiation with AI (role-play)	38 (51.4%)	36 (48.6%)	74

Table 3 presents the purposes for which students used AI during the preparation stage of negotiation training. The results indicate that the second objective—analyzing car-related information—was the most frequently used function (91.9%). The first objective followed this, planning negotiation strategies (60.8%), and the fourth objective, practicing negotiation through AI-supported role-play (51.4%). The third objective—receiving feedback from AI after negotiation—was used the least (40.5%).

These patterns directly address Objective 3 by identifying which AI functions students engaged with most during self-directed preparation. The high frequency of information analysis and strategy-planning functions suggests that students relied on AI primarily for tasks that provided immediate analytical structure for the negotiation scenario. In contrast, interactive features such as role-play and post-negotiation feedback were used less often. Because these results are descriptive, no inference is made regarding why students selected one AI function more frequently than another.

Overall, the usage patterns reflect a pragmatic approach to AI during out-of-class preparation, with students focusing on functions that offered clear, preparatory value for the negotiation task.

Table 4

Crosstabulation of AI Usage Objectives by Buyer and Seller (n = 74)

Objective	Party	Yes (%)	No (%)	n
Objective 1 – Plan negotiation strategies	Buyer	20 (54.1%)	17 (45.9%)	37
	Seller	25 (67.6%)	12 (32.4%)	37
Objective 2 – Analyze car-related information	Buyer	34 (91.9%)	3 (8.1%)	37
	Seller	34 (91.9%)	3 (8.1%)	37
Objective 3 – Receive feedback from AI after negotiation	Buyer	17 (45.9%)	20 (54.1%)	37
	Seller	13 (35.1%)	24 (64.9%)	37
Objective 4 – Practice negotiation with AI (role-play)	Buyer	20 (54.1%)	17 (45.9%)	37
	Seller	18 (48.6%)	19 (51.4%)	37

Table 4 shows that both buyers and sellers mainly used AI to analyze car-related information, with over 91% in each group citing this as their primary purpose. The second most common reason was planning negotiation strategies, reported by 67.6% of sellers and 54.1% of buyers, showing a slightly greater emphasis on strategic preparation among sellers. About half of both groups engaged in negotiation role-plays with AI (buyers = 54.1%; sellers = 48.6%). Receiving feedback from AI after negotiation was the least common purpose, especially among sellers (35.1%) compared to buyers (45.9%). Overall, the results suggest that students primarily used AI for analytical and planning purposes, with role-playing and feedback serving as secondary but still significant functions.

Table 5

Paired-Samples t-Test Results Comparing Perceived Negotiation Performance between Non-AI and AI Conditions (n = 74)

Condition	M	SD	95% CI [LL, UL]
Non-AI Satisfaction	3.78	0.58	[3.67, 3.91]
AI Satisfaction	4.45	0.42	[4.36, 4.55]
Difference (Non-AI–AI)	-0.67	0.62	[-0.82, -0.53]

Note. Paired-samples t-test: $t(73) = -9.23$, $p < .001$, Cohen's $d = -1.07$, Hedges' $g = -1.07$

The paired-samples t-test indicated a significant increase in perceived negotiation performance between the two conditions. A Wilcoxon signed-rank test was also conducted to assess consistency, and the nonparametric results were comparable to those from the t-test. Participants reported higher perceived negotiation performance in the AI condition (M = 4.45, *SD* = 0.42) than in the non-AI condition (M = 3.78, *SD* = 0.58). The mean difference of –0.67 was statistically and practically significant, with a large effect size (Cohen's d = –1.07). These findings support Hypothesis 1 in terms of the observed difference in perceived negotiation performance between the two sequential conditions.

Higher perceived negotiation performance was observed in the second round even though both negotiation rounds were completed outside the classroom. Because all students followed the same instructions, used the same scenario, and completed both rounds within a defined time window, the comparison across conditions was procedurally consistent. However, because the non-AI condition always preceded the AI-assisted condition, the observed increase cannot be attributed exclusively to AI-assisted preparation. Practice, familiarity with the scenario, or other order-related effects may also have contributed to the difference.

The convergence between the paired-samples t-test and the Wilcoxon signed-rank test further strengthens confidence in the observed difference across conditions, indicating that the improvement pattern was robust across both parametric and non-parametric analyses. This robustness is especially relevant given the independent nature of the out-of-class activity, where students engaged with the task without direct instructor supervision.

Table 6

Descriptive Statistics and Mixed ANOVA Results for Perceived Negotiation Performance by Condition and Party (n = 74)

Party	Condition	M	*SD*	95% CI [LL, UL]	Mean Diff. (AI – NoAI)	Cohen's *d*	Hedges' *g*
Buyer	Non-AI	3.75	0.54	[3.57, 3.93]			
	AI	4.43	0.44	[4.29, 4.58]	0.68 ↑	1.38	1.35
Seller	Non-AI	3.81	0.61	[3.61, 4.02]			
	AI	4.47	0.41	[4.33, 4.61]	0.66 ↑	1.26	1.24

For buyers, perceived negotiation performance increased from M = 3.75 (*SD* = 0.54) in the non-AI condition to M = 4.43 (*SD* = 0.44) in the AI condition, reflecting a mean increase of 0.68 points with a large effect size (Cohen's d = 1.38; Hedges' g = 1.35). For sellers, perceived negotiation performance increased from M = 3.81 (*SD* = 0.61) to M = 4.47 (*SD* = 0.41), a mean increase of 0.66 points with similarly large effect sizes (Cohen's d = 1.26; Hedges' g = 1.24). The mixed-design ANOVA confirmed a significant effect of condition, $F(1, 72) = 83.97$, $p < .001$, partial $\eta^2 = .54$, indicating a substantial difference in perceived negotiation performance across the two conditions. Neither the main effect of party nor the interaction between condition and party reached significance, indicating that the pattern of change did not differ significantly between buyers and sellers. These results support H2 in terms of comparable changes in perceived negotiation performance across negotiation roles.

The absence of an interaction effect indicates that the observed changes in perceived negotiation performance were not statistically different between buyers and sellers. However, this result should not be interpreted as evidence that AI reduced information asymmetry, equalized bargaining power, or provided objectively balanced support, because these constructs were not measured in the study. The substantial partial η^2 (.54) indicates a meaningful practical effect, showing that the difference between conditions was substantial in magnitude. While effect sizes of this magnitude are notable in a short negotiation exercise, the fixed sequence of the conditions means that the effect size represents the observed difference between the two rounds rather than an isolated causal effect of AI-assisted preparation.

The results therefore provide evidence of a substantial and role-independent difference in perceived negotiation performance between the two sequential conditions, supporting H3 in terms of effect magnitude. Although the study did not directly assess cognitive processes, the reported AI-use patterns show that students frequently used AI for information analysis and strategy planning during out-of-class preparation. These findings offer practical implications for negotiation pedagogy, indicating that AI-enabled preparation can serve as a valuable complement to traditional experiential learning activities.

Overall, the results consistently demonstrated higher perceived negotiation performance scores in the second, AI-assisted condition than in the preceding non-AI condition. Both the paired-samples t-test and the Wilcoxon signed-rank test confirmed the robustness of the observed difference, and the mixed-design ANOVA indicated that buyers and sellers showed

comparable patterns of change. Large effect sizes across both roles further underscored the magnitude of the observed difference between conditions. The analysis of AI-use purposes also revealed that students primarily relied on AI for information analysis and strategic planning, with interactive functions such as role-play and feedback used less frequently.

These findings provide a clear empirical foundation for the subsequent discussion. In the following section, the results are interpreted in relation to the study's objectives and existing literature. The discussion considers the observed differences in perceived negotiation performance, the comparable patterns across buyer and seller roles, and students' reported uses of AI, while accounting for the fixed order of the two conditions. The implications of these patterns for negotiation pedagogy and AI-supported experiential learning are also considered.

Discussions

The present study examined how artificial intelligence can enhance negotiation learning by focusing on improvements in students' perceived performance and their use of structured, analytical strategies during preparation. Grounded in the growing relevance of AI-supported pedagogy, the findings provide empirical evidence that AI tools can support more organized decision-making processes and strengthen students' preparedness for negotiation tasks. The principal contribution of the study is the examination of AI-assisted preparation within an experiential negotiation setting in which students remained responsible for conducting the negotiation themselves. The findings showed higher perceived negotiation performance in the second, AI-assisted condition, comparable patterns of change across buyer and seller roles, and frequent use of AI for information analysis and strategy planning. These findings extend previous research on AI-supported negotiation and human–AI learning by examining AI as a preparatory learning aid rather than as an autonomous negotiating agent (Atchley et al., 2024; Cummins & Jensen, 2024; Luo et al., 2024).

The results showed a notable difference in students' perceived negotiation performance between the two conditions. The paired-samples t-test revealed higher satisfaction scores in the AI-assisted condition, indicating a large effect size and suggesting that AI tools may offer valuable support during negotiation preparation and execution.

AI-assisted preparation may also serve as a form of formative practice, as instructors can use AI-generated outputs to provide more targeted feedback and promote reflective engagement. These interpretations align with previous work suggesting that AI can support structured analysis and planning in negotiation-related tasks (Cummins & Jensen, 2024; Li, 2024). AI may also support information organization and strategy development during negotiation planning (Cummins & Jensen, 2024; Falcão Filho, 2024).

The substantial effect size observed in this study provides strong support for H1. Although both negotiation rounds were conducted outside the classroom, students still demonstrated higher perceived performance scores in the AI-assisted condition. However, because all participants completed the non-AI condition first and the AI-assisted condition second using the same scenario, the observed difference cannot be attributed solely to AI-assisted preparation. Practice, familiarity with the scenario, or other order-related effects may also have contributed to the change. Because cognitive processes were not directly measured, interpretations related to mental strategy development should be treated cautiously.

The mixed-design ANOVA confirmed that both buyers and sellers showed higher perceived negotiation performance in the AI-assisted condition, with no significant condition × role interaction. This finding supports H2 and indicates that the pattern of change was comparable across the two negotiation roles. The absence of differential effects should not, however, be interpreted as evidence that AI provided equal bargaining power or objectively balanced support across roles, because these outcomes were not measured.

This distinction is particularly important in the used-car setting. Although sellers may possess more contextual information than buyers in actual used-car transactions, the present study did not measure participants' knowledge of vehicle condition or value, objective price benchmarks, final negotiated prices, or information asymmetry itself. The similar changes observed across buyer and seller roles therefore indicate comparable patterns of perceived performance rather than evidence that AI resolved information asymmetry or eliminated role-based advantages.

Students most frequently used AI to analyze car-related information (91.9%) and plan negotiation strategies (60.8%), with fewer using it for role-play practice or post-negotiation feedback. These usage patterns directly address Objective 3 and indicate that students relied on AI primarily for analytical and planning-oriented tasks. These patterns are consistent with applications of AI to information analysis and price-related decision support in negotiation and vehicle-related contexts (Liu & Zheng, 2020; Selvakanmani et al., 2024).

The relatively lower use of feedback and role-play features highlights an opportunity for instructional design to integrate AI more intentionally into interactive and reflective stages of negotiation training.

Large effect sizes (Cohen's $d > 1.0$) were observed for both buyers and sellers, supporting Objective 4 and indicating that the observed differences were not only statistically significant but also substantial in magnitude. Although the study does not examine negotiation efficiency or agreement outcomes, previous research suggests that AI support can facilitate more systematic preparation (Cummins & Jensen, 2024). In this study, the large observed differences in perceived performance suggest potential value for short-term negotiation training, although the fixed order of the two conditions prevents these differences from being interpreted as an isolated causal effect of AI-assisted preparation.

The use of student role-play should also be considered when interpreting these findings. The participants were undergraduate students performing assigned buyer and seller roles rather than actual used-car buyers or professional sellers. The simulation provided a standardized setting for experiential learning, but it could not fully reproduce the financial consequences, product knowledge, and information conditions of a real used-car transaction. The findings should therefore be interpreted as evidence from an educational negotiation simulation rather than as direct evidence of behavior in the used-car market.

The findings indicate that AI-assisted preparation can be incorporated into experiential negotiation training in ways that support information analysis, strategy preparation, and reflection. At the same time, interpretation of the observed gains should remain bounded by the self-reported outcome measure, the fixed sequence of conditions, the repeated scenario, and the simulated nature of the negotiation task. Broader practical implications, study limitations, and directions for future research are considered in the concluding section.

Conclusions

This study provides evidence that AI-assisted training can support negotiation learning in simulated used-car sales. The results show that students reported significantly higher perceived negotiation performance in the second, AI-assisted condition, while the pattern of change was comparable across buyer and seller roles. Students mainly used AI for its analytical and strategic planning capabilities, though interactive features such as role-playing and feedback were used less often. This highlights a practical yet underexplored aspect of AI's use in negotiation training: learners used its analytical functions more frequently than its interactive functions during preparation.

These outcomes are consistent with prior work showing that AI can support negotiation-related analysis, preparation, and decision processes (Cummins & Jensen, 2024; Li, 2024; Luo et al., 2024). However, limitations remain in the socio-emotional and relational dimensions of human–AI interaction (Kolomaznik et al., 2024). Therefore, while AI should not replace human negotiators, it can serve as a valuable tool for supporting preparation, information analysis, and strategy development in negotiation training. The present findings do not establish that AI closes information gaps or produces fairer negotiation outcomes because information asymmetry, bargaining power, and objective negotiation outcomes were not directly measured.

By examining its role in used-car sales, this study addresses a less-studied area of the existing research literature. It emphasizes the potential value of AI-assisted training in teaching consumer negotiation skills. The focus on a real-world, consumer-facing domain—rather than organizational bargaining or automated negotiation agents—offers an educational perspective on AI-assisted negotiation training. The used-car scenario should, however, be understood as a realistic and relatable simulation context rather than as a direct empirical test of information asymmetry in the used-car market. Future research could expand on these insights by exploring how AI can be better integrated into interactive practice, long-term skill development, and hybrid negotiation models that combine computational efficiency with human relational abilities.

In addition to negotiation training, this study illustrates how AI can be incorporated into experiential learning activities in social science and business education. Because critical thinking, ethical awareness, and fairness were not directly measured as study outcomes, the present findings should not be interpreted as empirical evidence that the intervention improved these attributes.

This research contributes to the intersection of negotiation education, social science pedagogy, and artificial intelligence. Theoretically, it positions AI as a potential pedagogical support tool rather than solely as a computational or autonomous negotiation agent. This approach broadens ongoing discussions on human–AI collaboration by considering how AI can be incorporated into experiential negotiation learning while retaining the learner’s responsibility for judgment and decision-making.

Methodologically, the study employs a quasi-experimental design that systematically compares AI-assisted and non-AI negotiation training within a consumer-focused simulation. Assessing both effect sizes and practical significance provides an indication of the magnitude of the observed differences in perceived negotiation performance across the two conditions. However, because all participants completed the non-AI condition first and the AI-assisted condition second using the same scenario, the design cannot isolate the effect of AI-assisted preparation from practice, scenario familiarity, or other order-related effects. This fixed

sequence represents an important limitation of the study and should be addressed in future research through counterbalanced or randomized condition sequences.

The study presents an instructional framework that integrates AI into negotiation preparation through information analysis, strategic planning, practice, and reflection. This framework may be useful for instructors seeking to incorporate generative AI into experiential negotiation activities while retaining direct student involvement in the negotiation process.

The simulated nature of the activity also limits the extent to which the findings can be generalized to actual used-car negotiations. The participants were undergraduate students performing assigned buyer and seller roles rather than experienced consumers or professional sellers, and the simulation did not reproduce the financial consequences, product knowledge, or relational pressures of an authentic transaction. Future research could therefore involve participants with actual buying or selling experience and incorporate objective negotiation outcomes in more realistic settings.

Generalizability is further limited by the use of students from a single course at one university and by the predominantly female sample. Replication across institutions, academic disciplines, demographic groups, and non-student populations would provide a stronger basis for assessing whether the observed patterns extend beyond the present sample.

Overall, this study's novelty lies in 1) applying AI-assisted training in a consumer negotiation context that remains underrepresented in current literature, and 2) providing empirical evidence of substantial differences in perceived negotiation performance between sequential non-AI and AI-assisted conditions in a self-directed, out-of-class experiential learning setting. These contributions extend existing research by showing how AI can function as a preparatory support tool within negotiation education.

In sum, the study provides evidence that AI-assisted preparation can be incorporated into experiential negotiation training to support information analysis and strategic preparation. The findings should nevertheless be interpreted within the boundaries of the self-reported outcome measure, fixed condition order, repeated scenario, simulated role-play, and restricted participant sample. Future studies using counterbalanced designs, objective negotiation outcomes, more diverse samples, and longer-term assessments are needed to determine more precisely the educational contribution of AI-assisted negotiation training.

Author Contributions

CP: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft Preparation, Writing – Review and Editing, Visualization, and Project Administration.

Declaration of the Use of Generative AI

During the preparation and revision of this manuscript, the author used ChatGPT (OpenAI, GPT-5.6) to assist with language editing, structural refinement, and revision of selected passages in response to reviewer comments. The tool was not used to generate or alter research data or to determine the statistical results. The author reviewed and revised all AI-assisted output, verified the accuracy of the content and references, and takes full responsibility for the final manuscript.

Ethics

The study was conducted in accordance with established ethical principles for educational research. Participation was voluntary, informed consent was obtained from all participants before data collection, and confidentiality of participant information was maintained throughout the study.

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Appendix

AI Bot Usage Log Form for Negotiation Preparation

Role Assigned: (Buyer / Seller)

AI Bot Used (e.g., ChatGPT, Gemini, Claude, etc.):

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1. Purpose of Using AI

   In which areas did you use AI assistance? (Check all that apply)

   ☐ Analyze car-related information

   ☐ Plan negotiation strategies

   ☐ Practice negotiation with AI (Role-play)

   ☐ Receive feedback from AI after negotiation

   ☐ Other (please specify):

2. Prompt(s) Used with AI

   Write down the main prompts or questions you asked the AI.

   Prompt(s) entered:

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3. AI Responses

   Summarize the responses provided by the AI or include the parts that you found most useful.

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4. Application of AI Insights

   - New strategies or ideas obtained from AI:

   - What you will apply in Round 2 negotiation:

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5. Additional Comments on AI Usage

   How did AI help your preparation? Were there any limitations you noticed?
