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**Original Research Article**

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# The Impact of AI-assisted Tool on the Practical Skill Performance of Accounting Students in Higher Education: An Empirical Study

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**Abstract**: The accounting profession is undergoing significant transformation driven by artificial intelligence (AI), creating an urgent need to modernize accounting education. However, traditional teaching methods often lack scalability and authentic contextualization for practical skill development. While AI-based teaching assistants show promise, empirical evidence of their effectiveness in accounting education remains scarce. This study investigates the impact of an AI-assisted tool on students' practical accounting skills. A quasi-experimental design was employed, involving 90 second-year accounting students assigned to an experimental group using an AI assistant or a control group receiving traditional instruction. The AI-assisted tool provided personalized feedback and adaptive exercises during a two-week intensive module. Results from independent samples t-test showed that the experimental group achieved significantly higher practical skill scores. Multiple regression analysis within the experimental group further revealed that self-efficacy, AI tool usage, and course satisfaction were significant positive predictors of performance. The study concludes that a well-designed AI teaching assistant can effectively enhance practical skill acquisition by acting as a dynamic scaffold. It highlights AI's role not only as a cognitive tool but as a multifunctional enabler that supports personalized, engaging, and effective skill development, offering valuable insights for innovating accounting pedagogy in the digital era.

**Keywords:** Artificial Intelligence; Accounting education; Practical skill; Empirical study

## 1. Introduction

The global accounting profession is undergoing a profound transformation driven by automation, data analytics, and artificial intelligence (AI). Intelligent technologies, such as AI-assisted tools are reshaping the roles of accountants, shifting the core focus from routine procedural tasks toward competencies requiring advanced analytical judgment, data interpretation, and strategic insight [1]. This evolution necessitates a corresponding advancement in accounting education to equip graduates with the sophisticated practical skills demanded by this new professional landscape [2, 3].

However, the current teaching of accounting skills within university environments faces several structural challenges. A primary tension exists between scalability and personalization [4, 5]. Given frequently imbalanced student-to-instructor ratios, educators struggle to provide timely, detailed, and differentiated feedback on individual students' practical work [6]. Furthermore, a significant lack of authentic contextualization persists. Traditional teaching tools, such as laboratory simulation software, often rely on fixed procedures and simplified scenarios. They fail to replicate the dynamic nature of real-world business environments, the ambiguity inherent in professional judgment, or the collaborative dynamics of human-AI work settings [7]. Consequently, students often find it difficult to transfer and apply learned knowledge to complex, unstructured problems.

Concurrently, the application of AI in higher education is deepening. AI technologies, particularly large language models, have demonstrated significant potential for creating interactive, dialogue-based intelligent teaching assistants [8]. Capable of providing 24/7 personalized learning support, adaptive content recommendation, and instant query resolution, such assistants have shown promise in fields like language learning and programming education [9]. Within business education, early explorations include customized AI tools for specific disciplines such as tax law and finance. Nevertheless, the deep integration of AI systems into accounting education remains in its nascent stages.

Critically, empirical research on the efficacy of AI-assisted tool in developing accounting skills is notably scarce. Existing literature predominantly consists of discussions on technical feasibility or preliminary case studies of application, lacking rigorous empirical examination of learning outcomes, underlying mechanisms, and long-term impacts. Specifically, there is a paucity of systematic evidence on how AI-assisted tool influences higher-order student competencies such as professional judgment and data analysis.

This study, therefore, aims to address this vital research gap. It employs an empirical approach to investigate whether and how an AI-assisted tool can effectively enhance the practical skill performance of accounting students, seeking to provide both theoretical foundation and practical guidance for innovating accounting pedagogy in the intelligent era.

## 2. Literature Review

### 2.1 The Evolution and Application of AI-assisted tool in Higher Education

The integration of AI into higher education has evolved significantly, shifting from early rule-based Intelligent Tutoring Systems to today's generative AI-powered teaching assistants [10]. These tools are increasingly recognized not merely as efficiency tools but as strategic responses to structural pressures in education, including the need for scalability, personalized learning, and adaptation to changing learner behaviors [11]. A 2025 study indicates that colleges need to open dialogue and collaboration among faculty members to develop shared guidelines and best practices for the ethical and effective use of AI in academic settings [12]. This pervasive use underscores the technology's transition from a novel concept to a core component of the academic.

Modern AI teaching assistants, particularly those built upon Large Language Models, offer transformative capabilities [13, 14]. They provide 24/7, interactive, and personalized learning support, enabling functions such as explaining complex concepts, generating practice questions, and offering immediate feedback on assignments. Empirical evidence from disciplines like programming education demonstrates their potential to enhance learning outcomes [15]. For instance, an AI tool providing hierarchical feedback was shown to help students overcome learning challenges, though its effectiveness varied with usage patterns and prior knowledge levels. These systems exemplify a broader trend: AI is reshaping the pedagogical landscape by taking over repetitive instructional tasks, thereby freeing educators to focus on higher-order activities such as fostering critical thinking and facilitating deep discussion [16, 17].

### 2.2 Specialized AI-assisted tools in Accounting Education

Within business education, the application of AI is advancing from general-purpose chatbots to deeply specialized, domain-specific models [18, 19]. This shift is driven by the need for accuracy, contextual relevance, and pedagogical alignment in professional fields [20, 21]. A prominent trend is the development of vertical large language models trained on massive, high-quality corpora of disciplinary knowledge.

The accounting discipline, characterized by strict standards, complex regulations, and a strong emphasis on practical judgment, has become a key area for such innovation [22]. Several universities launched dedicated accounting education platforms and models, marking the arrival of the "domain-specific model" era [23]. A landmark development is the AI model and its integrated platform released by Wu [24]. This platform is architecturally designed for educational effectiveness, covering the entire "teaching-learning-practice-assessment" chain and integrating intelligent assistants for theoretical dialogue, mistake analysis, and learning analytics. The model itself was trained on a vast corpus of authoritative accounting materials and professional questions, aiming to provide more reliable and precise knowledge services than general-purpose models.

Despite rapid technological adoption and promising case studies, the extant literature reveals several critical gaps that this study seeks to address. First, there is a lack of rigorous causal empirical evidence that clearly demonstrates the impact of AI-assisted tool on core accounting practical skills. Second, skill assessment methods are oversimplified, relying on final grades or subjective reports, which fail to distinguish between procedural proficiency and a deep conceptual understanding of underlying logic. Third, the specific pathways through which AI assistants influence learning remain a "black box" with the pedagogical effectiveness of key design features yet to be thoroughly examined. Finally, research has yet to adequately explore the potential of AI in developing higher-order cognitive skills such as strategic analysis and professional judgment.

## 3. Method

### 3.1 Research Design

This study utilized a quasi-experimental research design, specifically adopting a pretest-posttest control group structure, to rigorously examine the impact of an AI-assisted tool on the development of practical accounting skills. The design was selected to balance methodological rigor with practical feasibility in an authentic educational setting, where full random assignment of students was not administratively viable. The core objective of the study was to conduct a controlled comparison of learning outcomes between two distinct instructional conditions: an experimental group that received instruction integrated with a dedicated AI teaching assistant, and a control group that received equivalent instruction through conventional, non-AI-supported methods. To ensure the validity of this comparison, the study incorporated a pretest phase to assess and statistically control for participants' baseline proficiency in accounting practical skills, thereby isolating the effect attributable to the AI intervention from pre-existing differences between the groups.

### 3.2 Participants

The participant pool for this study consisted of 90 sophomore-year undergraduate students enrolled in an accounting program at a university in China. These students were naturally grouped into two parallel classes, each containing 45 individuals, which were following the same curriculum schedule and taught by the same instructor. To establish the experimental conditions, one intact class was randomly designated as the experimental group, while the other class served as the control group. Prior to the commencement of the intervention, all participants attended a comprehensive briefing session that detailed the research objectives, procedures, potential benefits, and confidentiality measures. Written informed consent was obtained from each student to formally confirm their voluntary participation in the study.

### 3.3 Procedure

The instructional intervention was implemented within a two-week intensive module dedicated to core accounting practical skills. To rigorously isolate the effect of the AI-assisted tool, both the experimental and control groups were taught identical curriculum content by the same instructor, thereby effectively controlling for potential confounding variables related to teaching style and curricular materials.

During this module, students in the experimental group utilized a purpose-built, AI-driven instructional assistant as an integral part of their learning process. This tool was designed to offer two primary forms of support: first, it provided automated, immediate evaluation and formative feedback on students' performance in practical tasks, highlighting errors and explaining correct procedures. Second, leveraging diagnostic insights from student performance, the system dynamically generated personalized practice exercises. These exercises were specifically tailored to address individual skill gaps, embodying an adaptive learning approach aimed at reinforcing competencies in a targeted manner.

In contrast, students in the control group completed the same module through a traditional instructional format. Their learning was facilitated via conventional methods, including instructor-led demonstrations of accounting procedures, supervised guided practice sessions, and receipt of standard feedback through manual review or generic commentary, without any integration of or access to the AI-assisted tool. This design ensured that the key variable distinguishing the two groups was the presence or absence of AI-facilitated, personalized support.

### 3.4 Measures and Data Collection

Data were collected from multiple sources at different time points. Before the intervention began, all participants completed a standardized accounting practical skills assessment to establish a baseline. An independent samples t-test confirmed no statistically significant difference between the two groups at the outset ($p > .05$), ensuring initial comparability. Upon completion of the two-week module, the final practical skills grades for all participants were obtained from the university's academic administration system as the primary outcome measure. Only students in the experimental group completed a detailed questionnaire after the module.

The survey instrument employed validated multi-item scales to measure three key constructs: course satisfaction, which assessed students' overall evaluation of the learning experience; self-efficacy in accounting practice, aimed at gauging their confidence in performing domain-specific tasks; and AI-assisted tool usage, capturing their perceptions of the AI-assisted tool usefulness and ease of use, as well as their frequency of interaction with it.

Quantitative data analysis was performed using SPSS 26. The analysis proceeded in two main stages. An independent samples t-test was conducted to determine if a statistically significant difference existed between the posttest practical skills scores of the experimental and control groups. For the experimental group only, a multiple linear regression analysis was performed. The posttest practical skills score served as the dependent variable. Key survey constructs—namely, AI-assisted Tool Usage, Course Satisfaction, and Self-Efficacy—were entered as independent variables to examine their relative influence on skill acquisition and to explore the extent to which engagement with the AI-assisted tool predicted learning outcomes.

This methodological approach allows for a robust evaluation of the AI-assisted tool's overall effectiveness while providing preliminary insights into the factors that may mediate its impact on student learning.

## 4. Results

### 4.1 Comparison of Practical Skills Performance

To assess the impact of the instructional intervention on student performance, an independent-samples t-test was conducted to compare the post-intervention practical skills scores between the experimental group and the control group. Descriptive statistics revealed a marked difference in outcomes: the experimental group ($N = 45$) attained a substantially higher mean score ($M = 89.29$, $SD = 5.78$) than the control group ($N = 45$, $M = 77.42$, $SD = 5.52$).

**Table 1.** Independent Samples Test

| | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|
| | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | Lower | Upper |
| Practical skills performance | 9.964 | 88 | 0.000 | 11.867 | 1.191 | 9.500 | 14.233 |

The results of the t-test confirmed a statistically significant difference between the groups, $t(88) = 9.96$, $p < .001$, as shown in **Table 1**. The assumption of homogeneity of variance was satisfied, as indicated by Levene's test ($F = 1.19$, $p = .279$). The mean difference between the experimental and control groups was 11.87 points, with a 95% confidence interval ranging from 9.50 to 14.23. This considerable and statistically significant disparity provides robust empirical support for the effectiveness of the AI teaching assistant, indicating that its integration into the accounting practical skills module was associated with a meaningfully greater enhancement in student performance compared to traditional instruction alone.

### 4.2 Factors Influencing Practical Skills Performance in the Experimental Group

To further elucidate the factors influencing skill acquisition specifically within the AI-supported learning context, a multiple linear regression analysis was performed on the experimental group data. The post-intervention practical skills total score served as the dependent variable, while Course Satisfaction, Self-Efficacy, and AI-assisted Tool Usage were entered as independent variables to assess their predictive power. The results are shown in **Table 2** to **Table 4**. Preliminary bivariate correlations confirmed strong, positive, and statistically significant relationships between the total score and each predictor (Course Satisfaction: $r = .837$, $p < .001$; Self-Efficacy: $r = .896$, $p < .001$; AI-assisted Tool Usage: $r = .856$, $p < .001$), justifying their inclusion in the model.

**Table 2.** Model Summary

| R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change | Durbin-Watson |
|---|---|---|---|---|---|---|---|---|
| 0.874 | 0.865 | 2.122 | 0.874 | 95.119 | 3 | 41 | 0.000 | 1.930 |

*Predictors: (Constant), AI-assisted tool usage, course satisfaction, self-efficacy*
*Dependent Variable: practical skill performance*

**Table 3.** ANOVA

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Regression | 1284.664 | 3 | 428.221 | 95.119 | .000[b] |
| Residual | 184.581 | 41 | 4.502 | | |
| Total | 1469.244 | 44 | | | |

*Predictors: (Constant), AI-assisted tool usage, course satisfaction, self-efficacy*
*Dependent Variable: practical skill performance*

**Table 4.** Coefficients

| | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | | Tolerance | VIF |
| (Constant) | 36.553 | 3.456 | | 10.575 | 0.000 | | |
| Course Satisfaction | 3.339 | 1.119 | 0.277 | 2.984 | 0.005 | 0.357 | 2.802 |
| Self-efficacy | 5.727 | 1.412 | 0.443 | 4.055 | 0.000 | 0.257 | 3.894 |
| AI-assisted tool usage | 2.620 | 0.920 | 0.288 | 2.850 | 0.007 | 0.301 | 3.322 |

*Dependent Variable: practical skill performance*

The full regression model was statistically significant, $F(3, 41) = 95.12$, $p < .001$, explaining a substantial 86.5% of the variance in practical skills performance (Adjusted $R^2 = .865$). The Durbin-Watson statistic of 1.93 indicated no significant autocorrelation in the residuals, supporting the independence of observations. Analysis of the standardized coefficients (Beta) revealed that all three constructs were unique and significant positive predictors. Self-Efficacy emerged as the strongest predictor ($\beta = .443$, $p < .001$), followed by AI-assisted Tool Usage ($\beta = .288$, $p = .007$) and Course Satisfaction ($\beta = .277$, $p = .005$). Diagnostic checks indicated moderate multicollinearity (VIF values ranged from 2.80 to 3.89), a common finding given the conceptual interrelatedness of these perceptual and behavioral variables; however, tolerance values all exceeded 0.1, confirming that multicollinearity did not substantially compromise the model's interpretability.

In summary, for students using the AI assistant, superior final performance was independently and collectively associated with greater confidence in one's accounting capabilities (self-efficacy), more frequent and favorable engagement with the AI-assisted tool, and higher overall satisfaction with the learning experience.

## 5. Discussion

This study yields robust empirical evidence affirming the efficacy of integrating a dialogic AI teaching assistant into accounting practical skills education. The central finding offers strong support for the proposed research hypothesis. This outcome aligns with a growing body of literature suggesting that AI-assisted tool can address persistent pedagogical challenges in skill-based disciplines, particularly the limitations related to scalability, individualized feedback, and interactive engagement in complex training environments [25-27]. Specifically, by delivering immediate, context-sensitive evaluations and generating adaptive practice pathways, the AI assistant appears to have operated as a dynamic scaffolding mechanism [18, 28]. Such scaffolding plausibly reduced extraneous cognitive load, thereby freeing learners' cognitive resources for the consolidation of schemas and the automation of procedures, which are critical for deepening skill acquisition.

These findings resonate with prior studies that highlight the role of AI in facilitating personalized and responsive learning environments. For instance, research by Sun, Cang [29] similarly observed that adaptive learning technologies enhanced procedural knowledge acquisition in STEM fields by providing tailored feedback loops. However, while previous studies often emphasized AI's utility in automating routine assessments, this study extends the discourse by illustrating its capacity to support dialogic and reflective practice. Conversely, the study by Lin, Lin [30] contrast with some earlier works that reported limited effects of AI-assisted tool s on higher-order skills when used without guided integration into the curriculum. Unlike those implementations, the AI assistant in this study was embedded within a structured pedagogical framework, suggesting that contextual alignment and instructional design are critical moderators of technology's educational impact. Thus, while corroborating the broader potential of AI in education, this study also underscores the discipline-specific and design-dependent nature of its effectiveness, contributing a more nuanced understanding to the ongoing scholarly conversation.

The regression analysis conducted within the experimental group provides further nuanced insight into the mechanisms through which the AI teaching assistant influences learning outcomes in accounting practical skill acquisition. The model identified three significant and interrelated predictors of final performance: Self-Efficacy, AI Tool Usage, and Course Satisfaction. The dominance of self-efficacy as the strongest predictor reinforces the central role of learners' belief in their own capabilities—a finding consistent with Bandura's social cognitive theory. This suggests that the AI tool may have facilitated mastery experiences by offering achievable, personalized challenges and reinforcing positive feedback, thereby strengthening confidence that subsequently enhanced performance. Such a result aligns with prior research by Sabatini, Graesser [31], who proposed a need to develop adaptive instruction that spans the development of proficiency from preschool to college levels. However, while their study focused on general software training, the present research extends this understanding to the highly structured and regulation-driven context of accounting, highlighting how domain-specific AI scaffolding can cultivate confidence in applying complex professional standards.

The significant predictive value of AI-assisted Tool Usage underscores that mere technological access is insufficient; rather, the perceived usefulness of the tool and the depth of engagement with its features serve as key mediators of its educational effectiveness. This echoes the findings of Sivajyothi, Salma [32], who found the key factors affecting employability as well as the requirements of the new job market may be helpful to all educational institutions.. Yet, our study diverges from earlier works that reported limited skill transfer when AI was used passively (e.g., Wilson & Kumar, 2021). Here, the AI system actively shaped the learning trajectory by generating contextualized practice and real-time feedback. This distinction highlights the importance of AI's role in guiding practice rather than merely delivering content, particularly in skill-based education where procedural fluency and judgment are essential.

Furthermore, the role of Course Satisfaction indicates that a positive affective response to the AI-enhanced learning environment contributed to motivation and sustained engagement, fostering a virtuous cycle that supported skill development. This triangulation of cognitive (self-efficacy), behavioral (tool usage), and affective (satisfaction) factors offers a more holistic framework for understanding how AI-assisted tools influence learning beyond simple knowledge transmission. Importantly, this integrated perspective aligns with the study by Zhang, Wu [33], who argued that successful technology integration requires attention to pedagogical. However, whereas their work focused on broad blended learning environments, the current study delineates how AI-assisted tool can simultaneously address these dimensions within a focused skill-building context—personalizing the learning process while also enhancing emotional and cognitive engagement.

In summary, these findings illustrate a dynamic interplay in which meaningful interaction with a well-designed AI-assisted tool can concurrently elevate self-efficacy and course satisfaction, creating a mutually reinforcing loop that amplifies practical skill acquisition. This positions AI not only as a cognitive tool but as a multifunctional enabler in accounting education that capable of delivering personalized scaffolding, fostering confidence, and enriching the overall learning experience in ways that traditional methods often cannot scale effectively.

## 6. Implications

The findings of this study carry significant implications for multiple stakeholders in higher education, extending beyond mere validation of a technological tool to offering actionable insights for educational practice, institutional strategy, and academic research.

For University Administrators, the results offer compelling evidence to inform strategic decision-making and resource allocation. The study demonstrates that a well-designed, domain-specific AI-assisted tool can act as a pedagogical force multiplier, enabling scalable, personalized skill development that is often logistically and financially unfeasible through traditional means. This supports the case for investing in the development or procurement of subject-matter-specific educational technology rather than relying on generic tools. Furthermore, it highlights the importance of creating supportive ecosystems for innovation, including faculty training programs, technical support infrastructure, and policies that encourage the ethical and effective integration of such tools into the curriculum.

For Educators, the practical implications are direct and transformative. The AI-assisted tool effectively offloads routine, time-intensive tasks such as initial performance evaluation and provision of basic corrective feedback. This liberation from repetitive labor allows instructors to reallocate their expertise and time toward higher-value educational activities. Teachers can focus more on facilitating deep, Socratic discussions, mentoring students through complex conceptual and ethical dilemmas, designing richer collaborative projects, and providing nuanced, personalized guidance that AI cannot replicate. Thus, the tool does not replace the educator but redefines their role as a facilitator of critical thinking and complex problem-solving.

For Researchers, this study provides a substantive contribution by moving beyond descriptive accounts of AI in education. It empirically delineates specific psychological and behavioral pathways through which AI influences complex skill acquisition. By connecting AI-assisted learning to established educational frameworks like Bandura's social cognitive theory and Cognitive Load Theory, it offers a mechanistic, theoretically-grounded model for future inquiry. This enables researchers to formulate more precise hypotheses and design studies that investigate not just if AI works, but how and under what conditions it is most effective, particularly in structured professional disciplines like accounting.

## 7. Limitations

This study has several limitations that chart a course for future inquiry. First, the sample was drawn from a single university, which may limit the generalizability of the findings. Future multi-institutional studies are warranted. Second, the intervention period was relatively short. Longitudinal research is needed to examine the durability of skill gains and the long-term impact on professional readiness. Third, while the regression model is informative, the quasi-experimental design cannot definitively establish the causal direction of the relationships between self-efficacy, satisfaction, and performance. Experimental and mixed-methods studies that manipulate these variables are encouraged.

## 8. Conclusion

In conclusion, this research substantiates the transformative potential of AI teaching assistants in accounting education, positioning them not merely as supplementary tools but as catalytic enablers of pedagogical innovation. By delivering robust empirical evidence of significant skill improvement, this study demonstrates that AI can effectively address long-standing structural challenges in skill-based education. More importantly, by elucidating the synergistic relationships among self-efficacy, active tool engagement, and course satisfaction, it reveals that AI's impact extends beyond cognitive gains to encompass motivational and affective dimensions of learning, thereby fostering a more holistic and sustainable developmental process.

The AI-assisted tool, through its capacity to provide adaptive, dialogue-based, and context-sensitive support, functions as a dynamic learning partner that scaffolds complex skill acquisition in ways traditional methods cannot easily replicate. It empowers students to learn through immersive simulation, reinforces confidence via mastery-oriented tasks, and sustains engagement through responsive interaction.

As AI technology continues to advance, its thoughtful integration into accounting education holds compelling promise. It enables a shift from a teacher-centered, one-size-fits-all model to a learner-centered, personalized, and interactive paradigm, better preparing future accountants to navigate the data-driven, digitally integrated, and ethically nuanced landscape of modern professional practice. Ultimately, this study affirms that AI, when strategically embedded within curriculum and pedagogy, can serve as a pivotal force in the ongoing evolution of accounting education toward greater efficacy, inclusion, and relevance.

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## Appendix: Survey Questionnaire

Dear Participant,

You are invited to participate in a research study. This survey is a crucial component of this research. Your participation will involve completing this questionnaire. Your responses are completely anonymous and confidential. The data will be used solely for aggregated academic analysis and will not be used to identify you individually.

Thank you for your valuable contribution.

1. **Student ID:** ______
2. **Gender:**
   ○ Male
   ○ Female
3. **Prior experience with using AI tools for learning:**
   ○ Never
   ○ Rarely
   ○ Occasionally
   ○ Frequently
   ○ Very Frequently

*Please indicate your level of agreement with the following statements based on your experience.*

Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| CS1 | The instructional content of the practical skills module was clear and well-organized. | | | | | |
| CS2 | The teaching methods used helped me understand the accounting procedures effectively. | | | | | |
| CS3 | The learning resources provided were sufficient and helpful. | | | | | |
| CS4 | I received adequate feedback on my practical work to improve my skills. | | | | | |
| CS5 | The overall difficulty level of the module was appropriate. | | | | | |
| SE1 | I can analyze complex business transactions and determine the correct accounting entries. | | | | | |
| SE2 | I can independently prepare key financial statements. | | | | | |
| SE3 | I can interpret financial statements to assess a company's performance. | | | | | |
| SE4 | When faced with a new accounting problem, I am confident I can learn how to solve it. | | | | | |
| SE5 | I believe I have the necessary skills to succeed in an accounting internship or entry-level position. | | | | | |
| AU1 | I often use the AI-assisted tool for learning activities. | | | | | |
| AU2 | I can use the AI-assisted tool effectively for accounting practice tasks. | | | | | |
| AU3 | I believe the AI-assisted tool is useful for improving my accounting skills. | | | | | |

Thank you very much for your time and honest responses. Your input is greatly appreciated.