

AI Teaching Tool Engagement and Academic Performance in Undergraduate Accounting: Associations and Moderators

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This study explores the impact of AI teaching tools on academic performance in undergraduate accounting courses, considering student personality traits, grit, prior academic standing, and sex. Using actual usage data from AI platforms in Financial and Management Accounting, alongside personality and grit assessments, we found that AI engagement was positively associated with academic improvement primarily among students with lower perseverance of effort. This moderating effect was significant in the first semester but not the second. Additionally, students from higher-standing academic departments showed greater improvement with AI tool use. No significant moderation by sex was observed. These findings suggest that AI teaching tools may provide targeted support for students who struggle with sustained effort, informing the strategic integration of AI in accounting education to enhance learning outcomes for diverse student populations.

Keywords: Artificial intelligence, academic performance, accounting education, personality traits, grit.

Introduction

The World Economic Forum (2024) acknowledges the rapid acceleration of technology and emphasizes the need for education systems to adapt, preparing students for future opportunities and risks. Artificial intelligence (AI) and adaptive digital platforms are increasingly used to provide individualized practice, immediate feedback, and learning analytics. These features are especially pertinent in introductory accounting courses, where students often have varied academic backgrounds and may struggle to maintain consistent effort when faced with a sequence of interconnected technical concepts (Malik et al., 2025).

However, the educational value of such platforms cannot be assumed solely based on their adoption. Students who excel in platform activities may already have greater subject knowledge, higher prior achievement, stronger motivation, or better study discipline. Additionally, scores from these platforms often reflect a combination of factors, such as achievement, completion, effort, repeated attempts, and responsiveness to feedback, rather than pure academic mastery. Therefore, observational research must distinguish between mere exposure to a platform, active behavioral engagement with it, and actual achievement resulting from its use.

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The advent of AI has prompted significant discussion regarding its potential impact on accounting education (Brink & Reichert, 2020; Holmes & Douglass, 2022). While some studies have explored the possible benefits of AI in accounting education from the educators' perspective (Fachrurrozie et al., 2025), students' perceptions of AI teaching tools (Malik et al., 2025), or its role in increasing student engagement (Lakshmi et al., 2023), Wood et al. (2023) note that the actual impact has been "relatively modest" (p. 3) in practice, often limited to theoretical discussions (Dai, 2025; Fitria, 2021) or the emergence of models such as ChatGPT (Ballantine et al., 2024; Sundkvist & Kulset, 2024).

This study offers an original contribution to the literature by empirically investigating the actual use of AI teaching tools in introductory Financial and Management Accounting subjects and its association with student academic performance. Unlike previous research that often focuses on perceptions or general factors influencing interest in accounting (Djatej et al., 2015; Jackling & Calero, 2006; Sadri & Robertson, 1993), this study uniquely incorporates the non-cognitive construct of grit, a personality trait reflecting perseverance and passion for long-term goals (Duckworth et al., 2007), as well as six personality dimensions measured via the HEXACO inventory (Ashton & Lee, 2007). We examine how students' individual grit levels and personality dimensions interact with their engagement with AI teaching tools to influence their final academic marks. This approach moves beyond simply measuring engagement or beliefs about employability (Awadallah & Elgharbawy, 2020; Kim et al., 2002; Samsuri et al., 2016) to develop a deeper, more nuanced understanding of student success in AI-enhanced learning environments.

The research was conducted in compulsory first-year Financial and Management Accounting subjects across three different majors (Finance, Management, Hospitality) at a public university in Cyprus. By analyzing students' grit and personality traits alongside their engagement with the AI teaching tool and their final marks, this paper provides novel insights into how individual psychological characteristics influence learning outcomes in technology-mediated environments.

Literature Review

Theoretical Framework and Conceptual Foundations

This study draws upon Self-Regulated Learning (SRL) theory and Social Cognitive Theory (SCT). SRL theory (Zimmerman, 2000) posits that learners actively engage in their own learning through cognitive, metacognitive, and motivational strategies. AI tools support SRL through adaptive feedback mechanisms and personalized learning paths. SCT (Bandura, 1986) emphasizes reciprocal determinism, wherein personal factors (grit, personality traits), environmental factors (AI tools), and behaviors (engagement) interact dynamically. Within this framework, a student's personality traits and grit act as personal factors that moderate engagement with AI-enhanced environments.

Research shows that specific personality traits significantly predict university students' attitudes toward generative AI (GAI) and their engagement in GAI-related

academic misconduct (Bano et al., 2019; Liang et al., 2025; Song & Liu, 2025). Liang et al. (2025) found that Extraversion and Openness to Experience were positive predictors of favourable attitudes toward GAI, meaning students higher in these traits were more receptive to using AI tools in their academic work. Conversely, Honesty-Humility, Agreeableness, and Conscientiousness emerged as significant negative predictors of GAI misconduct, indicating that students with higher levels of these ethical and self-disciplined traits were less likely to misuse AI for cheating or plagiarism. Importantly, personality traits were found to be stronger and more direct predictors of unethical AI behavior than attitudes toward AI themselves, suggesting that deep-seated dispositional factors may override surface-level beliefs when students decide whether to exploit AI tools (Liang et al., 2025).

Furthermore, the concept of grit, as defined by Duckworth et al. (2007), is a crucial non-cognitive trait that predicts success beyond talent. It encompasses two facets: perseverance of effort and consistency of interest toward long-term goals. Understanding how grit interacts with AI teaching tools is vital, as AI's adaptive nature may differentially impact students based on their inherent levels of perseverance. For instance, AI tools could provide the scaffolding necessary for low-grit students to maintain effort, while high-grit students may leverage AI for advanced challenges.

The Changing Landscape of Accounting Education

The accounting profession and its educational foundations are undergoing significant transformations. Researchers have consistently highlighted concerns regarding the "accounting student pipeline," the perceived difficulty of accounting as a subject, and the current state of accounting education (Holmes et al., 2022; Holmes & Douglass, 2022; Dawkins, 2023; Dennis, 2023). Boyce (2018, pp. 377–379) noted that meaningful development and reform needs in accounting education have remained largely unaddressed for over five decades. While some progress was observed in the 1990s and 2000s, it was often isolated to specific institutions, allowing a "crisis in accounting education" to persist (Gabbin, 2002; Sundem, 2014).

This persistent challenge underscores the pressing need for accounting education to adapt to the demands of society, the profession (Zamaina & Subramanian, 2024), and the rapidly changing technological landscape. Ballantine et al. (2024) argue that higher education's role in fostering critical and creative individuals has been neglected, and advocate for an approach that balances technical accounting skills with student-centered, humanistic, and formative development.

The effective integration of AI can make accounting education more engaging and relevant, thereby enhancing the skills and reflexivity required to understand complex accounting concepts. Consequently, accounting graduates increasingly need to possess not only technical proficiency, but also soft skills, critical thinking, sound professional judgment, and a nuanced understanding of accounting (Boyce et al., 2001; Dillard & Vinnari, 2017; Douglas & Gammie, 2019; Ballantine et al., 2024). Stimulating students' interest in accounting through innovative pedagogical approaches, such as AI integration, is crucial for increasing enrolment and addressing the accounting pipeline issue (Malik et al., 2025). Accounting educators must

therefore align technology skills with learning objectives within the curriculum to meet evolving business demands (Akbulaev et al., 2021; Vachkova et al., 2022) and facilitate holistic student engagement in the learning process (Xiao & Foster, 2024).

AI in Tertiary Education: Pedagogical Skill Development

The broader educational system has seen a growing interest in the application of AI. AI in education encompasses a wide range of applications, from intelligent tutoring systems and adaptive learning platforms to automated assessment and personalized feedback (Wang et al., 2024). It is important to distinguish between the educator's use of AI tools (e.g., for administrative tasks, content creation, or analytical insights into student performance) and the student's use of AI tools (e.g., for learning, practice, or self-assessment). This study primarily focuses on the student's direct engagement with AI teaching tools designed to facilitate their learning.

AI teaching tools are designed to enhance pedagogical skill development by offering personalized learning experiences, immediate feedback, and adaptive content (World Economic Forum, 2024). These tools can tailor instruction to individual learning paces and styles, providing targeted support where students struggle and advanced challenges where they excel. However, the effectiveness of these tools is not uniform and depends on various factors, including the design of the AI, the pedagogical context, and individual student characteristics.

Established scholarship on technology-mediated learning in accounting education provides a foundation for understanding the current integration of AI (Theuri et al., 2024). Early integration efforts date back decades (Baldwin-Morgan, 1995; Christopher, 1996; Bao, 2019), demonstrating a long-standing interest in leveraging advanced technologies in the discipline. More recent studies continue to explore how AI can enhance student engagement (Abou-El-Sood, 2025a, 2025b; Hu et al., 2024). Critical perspectives on the use of AI in accounting education, highlighting both promises and pitfalls, are also emerging (Ballantine et al., 2024).

AI in Accounting Education: Research Gaps

Within accounting education, AI teaching tools are increasingly being adopted to address specific learning challenges and prepare students for an AI-driven professional landscape. These tools range from intelligent tutoring systems for foundational accounting principles to AI-powered simulations for complex financial analysis.

While the potential of AI in accounting education is widely acknowledged, research has largely concentrated on educators' perspectives (Fachrurrozie et al., 2025), students' perceptions of AI benefits (Malik et al., 2025), or general increases in student engagement attributed to AI (Lakshmi et al., 2023). A significant gap remains in understanding the direct impact of actual student engagement with AI teaching tools on academic performance, particularly when individual student characteristics are considered. Specifically, there is a paucity of research that empirically investigates the interplay between personality traits, grit, actual AI tool usage, and subsequent academic outcomes in accounting subjects. The present study addresses this gap.

The Role of Personality Traits, Grit, and Sex in Academic Performance

Personality traits, particularly those outlined in the HEXACO model, include Honesty-Humility, Openness to Experience, Emotionality, Extraversion, Agreeableness, and Conscientiousness, and these have been shown to influence students' learning behaviors, motivation, and persistence (Jia et al., 2022). Ashton and Lee (2009) designed a self-referenced questionnaire measuring these six dimensions. Understanding how AI teaching tools interact with different levels of these individual student personality characteristics is crucial for designing inclusive and effective learning environments (Arpaci et al., 2025).

Grit has emerged as a significant predictor of success in various domains, including academic achievement (Duckworth et al., 2007; Duckworth & Gross, 2014). Defined as perseverance and passion for long-term goals, grit enables individuals to sustain effort despite setbacks and challenges. In educational contexts, students with higher grit are more likely to engage in deliberate practice, seek help when needed, and persist in difficult tasks — all of which contribute to better academic outcomes (Duckworth et al., 2007; Eisenberg et al., 2014; Kovacevic et al., 2025; Mittal et al., 2024). Conversely, students with lower grit may be more prone to disengagement when faced with academic challenges. This raises the important question of whether AI tools, with their adaptive scaffolding features, meaning structured support and guidance tailored to the learner's needs, may compensate for lower grit by sustaining engagement.

The role of sex in academic performance and technology adoption has also been a subject of extensive research. While some studies suggest sex-based differences in learning styles, technology comfort, or academic outcomes, these findings are often context-dependent and influenced by cultural, social, and pedagogical factors (Bajaj et al., 2021; Fachrurrozie et al., 2025; Lu & Chiou, 2010). In the context of AI teaching tools, it is important to investigate whether sex plays a role in how students engage with these tools or how their academic performance is affected, to ensure equitable and effective educational experiences. These three converging gaps, the role of actual AI engagement, the moderating function of grit and personality traits, and the potential influence of sex and prior academic standing, motivate the four hypotheses that follow.

Research Objectives and Hypotheses

The aim of this paper is to investigate whether the use of AI teaching tools in undergraduate accounting subjects is associated with higher final marks, and whether this association is moderated by individual student characteristics, specifically, grit, personality traits, prior academic standing, and sex. Based on the theoretical framework and existing literature, we formulate the following hypotheses.

H1: There is a positive association between students' engagement with AI teaching tools and their academic performance in undergraduate accounting subjects.

Zhang and Zhao (2022) found that utilizing AI-assisted education in accounting courses increases student participation and performance. This study tests whether the same relationship is held in both Financial and Management Accounting subjects within the same population.

H2: There is no significant difference in academic performance between male and female students using AI teaching tools in undergraduate accounting subjects.

Fachrurrozie et al. (2025) found that the sex variable can influence intentions to use AI tools but identified no moderating effect between sex and performance. This study extends that line of inquiry by explicitly testing sex as a moderator of the AI engagement–performance relationship.

H3: Students with higher prior academic achievement will demonstrate greater academic improvement in undergraduate accounting subjects when using AI teaching tools.

Wecks et al. (2024) found that students with higher learning potential may be negatively affected by the use of generative AI tools (e.g., ChatGPT) in terms of exam performance. However, that finding pertains specifically to generative AI and exam-taking rather than to adaptive AI teaching platforms designed to support formative learning. This hypothesis tests whether students with higher prior academic standing benefit more from structured AI-assisted learning.

H4: Students' grit moderates the relationship between their engagement with AI teaching tools and their academic performance, such that the association between AI engagement and performance differs across levels of grit.

Prior research has not established a clear directional prediction for this moderation effect. On one hand, high-grit students may leverage AI tools to achieve even higher performance through deliberate, sustained practice. On the other hand, low-grit students may derive disproportionate benefit from the scaffolding, adaptive feedback, and structured guidance that AI tools provide, effectively compensating for lower perseverance. This study tests both possibilities as moderated regression.

Method

Study Design

This exploratory study employed a quantitative, correlational design to investigate the relationships between AI teaching tool engagement, student characteristics (grit, personality traits, prior academic standing, and sex), and academic performance in undergraduate accounting subjects. The study was conducted over two academic semesters (Semester 1 and Semester 2) during the 2024–2025 academic year at a

public university in Cyprus. Ethical clearance was obtained from the National Bioethics Committee in February 2025 (Approval No. EP2025-01-60). All data were anonymized and handled in accordance with ethical guidelines to ensure participant privacy and confidentiality.

The participants were first-year undergraduate students enrolled in compulsory introductory Financial Accounting (semester 1) and Management Accounting (semester 2) subjects. These subjects are foundational for students across three majors: Finance, Management, and Hospitality. All students were required to use a specific AI teaching tool as an integral part of their coursework. This design, while not including a control group without AI, allowed for an in-depth examination of how individual differences interact with AI tool usage within a real-world educational setting. The focus was on analysing associations and moderation effects, rather than establishing causal improvements relative to traditional instruction.

Participants

A total of 134 students were enrolled in the study. Of these, 30 were excluded from the final analytic sample due to missing data (e.g., students who did not provide identity numbers, preventing linkage of grit and personality scores with academic records), yielding a final analytic sample of $N = 104$ (22 male, 82 female). Participants ranged in age from 18 to 20 ($M = 19.1$, $SD = 1.2$) and distribution across majors' tracks: Finance ($n = 31$), Management ($n = 35$), and Hospitality ($n = 38$). Participation was voluntary, and informed consent was obtained from all participants.

AI Teaching Tool Description and Integration

The AI teaching tool utilized in this study was McGraw-Hill Connect® (hereafter referred to as "Connect"). Connect is an adaptive online learning platform designed to provide personalized learning experiences and assessment opportunities. Key features relevant to this study include:

1. Adaptive Practice: The platform offers adaptive practice problems and quizzes that adjust in difficulty based on student performance, providing immediate feedback and guiding students to master targeted concepts.
2. SmartBook: An interactive e-textbook that uses AI to identify knowledge gaps and direct students to relevant sections for review, optimizing study time.
3. Algorithmic Problems: Connect generates a large pool of algorithmic problems, ensuring that students receive unique practice opportunities and reducing the potential for rote memorization.
4. Performance Analytics: The platform tracks student progress, engagement, and performance across various tasks, providing data that can be used by both students and instructors to identify areas requiring improvement.

The tools provided by the publisher can be classified as supporting holistic AI literacy (see Dai, 2025) and fulfilled Bao's (2019) theoretical model of AI in accounting instruction. The AI tools incorporated both "plugged" (technology-mediated) and

"unplugged" (conceptual, device-free) components (Long & Magerko, 2020; Ng et al., 2023). Following Biggs (1999, 2014) and Christopher (1996), the lead instructor — an accounting professor — first identified the learning objectives for each chapter; Connect then provided a curated set of questions for each student to complete. When a student answered incorrectly, the system redirected them to the relevant section of the textbook for further reading before allowing a reattempt, with a maximum of three attempts per question. Weekly assessment scores were used to constitute the internal assessment component (20% of the final mark) and to inform the instructor on which learning objectives required revisiting. Connect also generated midterm practice quizzes and final exam practice sets based on instructor-specified parameters.

Connect was integrated as a mandatory component in both subjects. Students were required to complete specific assignments, quizzes, and practice modules within the platform, and their performance within the tool directly contributed to their academic standing. It is important to note that while AI scores contributed to the final grade, the actual midterm and final examinations were independently designed by the instructors. The AI system did not generate the midterm or final examination questions, thereby minimizing circularity between AI metrics and overall performance outcomes.

Measures

Academic performance was operationalized using three assessment components. The AI tool score constituted 20% of the total grade; the midterm examination constituted 30%; and the final examination constituted the remaining 50%. Final percentage grades were recorded for each of the two semesters.

AI teaching tool engagement was measured by students' performance on AI-generated assessments within the Connect platform. These were recorded as two separate scores, one per semester, reflecting students' proficiency and effort on the adaptive learning tasks and assigned modules within the AI environment.

Personality traits were measured using the HEXACO Personality Inventory (Ashton & Lee, 2009), which assesses six major dimensions: Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience. Students responded to items on a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree). The HEXACO has demonstrated strong reliability and validity across diverse cultural contexts (De Vries et al., 2008).

Grit was measured using the validated 12-item Grit Scale (Duckworth et al., 2007), which assesses two facets: perseverance of effort and consistency of interest. Students responded to items on a 5-point Likert scale (1 = Not at all like me to 5 = Very much like me). The total score provided a continuous measure of each student's overall grit level.

Prior academic standing was operationalized through midterm scores, as a proxy for prior academic achievement. Students enrolled in Finance typically enter with higher academic credentials than those in Management, who in turn typically enter with higher credentials than those in Hospitality and Tourism Management, consistent with differential admission standards across these majors.

Sex was collected as a self-reported categorical variable (Male/Female).

Results

Table 1 presents descriptive statistics for all key variables. The final analytic sample comprised 104 students (78.8% female, 21.2% male). The mean grit score was 3.32 (SD = 0.54), with subscale means of 3.40 (SD = 0.84) for Perseverance of Effort and 3.24 (SD = 0.82) for Consistency of Interest, indicating a moderate level of grit without evidence of ceiling or floor effects. Three participants had missing responses on the Grit and HEXACO measures; because these cases could not be included in analyses involving those variables, models including Grit were estimated on 101 participants (listwise deletion), whereas analyses not involving Grit or personality scores used the full sample of 104.

Table 1. Descriptive Statistics of Key Variables

Variables	Mean	S.D.	Min.	Max.
AIsem1	14.65	4.76	0	20.00
Midterm1	17.19	4.42	0	28.20
Final1	23.9	8.81	0	48.00
AIsem2	7.90	5.50	0	19.00
Midterm2	18.44	5.33	7.00	29.00
Final2	31.44	7.71	11.00	45.00
Grit	3.32	0.54	1.92	4.75
Grit_per	3.40	0.84	1.00	5.00
Grit_con	3.24	0.82	1.00	5.00
HEXACO_HH	3.39	0.69	2.00	5.00
HEXACO_Em	3.17	0.72	1.40	4.50
HEXACO_Ag	3.00	0.60	2.00	4.20
HEXACO_Co	3.41	0.64	2.20	4.70
HEXACO_OE	3.10	0.73	1.70	4.80
HEXACO_Ex	3.20	0.59	1.70	4.60

Note: Min=Minimum, Max= Maximum, AIsem1= AI score for first semester, AIsem2= AI score for second semester, Grit = total grit score; Grit_per = Perseverance of Effort, Grit_con= Consistency of Interest, HEXACO_HH= Honesty-Humility, HEXACO_Em= Emotionality, HEXACO_Ag= Agreeableness, HEXACO_Co= Conscientiousness, HEXACO_OE= Openness to Experience, HEXACO_Ex= Extraversion.

An Exploratory Factor Analysis (EFA) was conducted on the 12-item Grit Scale using Maximum Likelihood (ML) estimation and promax (oblique) rotation. The scree plot and model fit statistics supported a two-factor solution, consistent with the theoretical conception of Grit as comprising two related but distinct facets. The two-factor solution accounted for 40% of the total variance. The factors were moderately correlated ($r = 0.24$), indicating they measure distinct but related constructs. Items intended to measure "Consistency of Interest" loaded saliently on the first factor, and items intended to measure "Perseverance of Effort" loaded saliently on the second factor. One item (Item 11) demonstrated cross-loadings on both factors, though more strongly on "Consistency of Interest." Model fit was

adequate to good: RMSEA = 0.048 (90% CI [0.00, 0.08]); TLI = 0.945. Reliability was high, with factor score-factor correlations of 0.91 for both facets.

A second EFA was conducted on the 60-item HEXACO inventory using ML estimation and promax rotation, yielding six factors that collectively accounted for 29% of the total variance. Inter-factor correlations estimated by EFA were generally low to moderate ($|r|$ range: 0.02-0.22), supporting relative factor independence. The EFAs were used to examine the structure of the instruments; in the subsequent analyses, Grit, its two facets, and the six HEXACO dimensions were represented by scale scores (the mean of the items for each scale), with reverse-keyed items recoded. The pattern of factor loadings provided mixed support for the theoretical structure: while several factors captured their intended constructs, a notable proportion of items exhibited weak, complex, or unexpected loadings, with low communalities suggesting suboptimal fit of the six-factor model in this sample. This interpretation is corroborated by the TLI of 0.592, which falls below conventional thresholds for acceptable fit; however, the RMSEA of 0.048 (90% CI [0.042, 0.054]) indicated reasonable error of approximation. Despite overall modest model fit, factor score reliabilities were acceptable (factor score-factor correlations ranged from 0.89 to 0.92).

All subsequent analyses were conducted using SPSS (Version 31). Preliminary screening confirmed that the skewness and kurtosis of all variables fell within the ± 2 range, indicating approximate normality. Factor scores from both EFAs were used in subsequent moderation analyses.

H1: Association Between AI Tool Engagement and Academic Performance

Pearson correlation coefficients between AI scores and examination results are presented in Table 2. AIsem1 was significantly and positively correlated with Midterm1 ($r = 0.25$, $p < .05$) and Final1 ($r = 0.33$, $p < .01$) and was moderately correlated with AIsem2 ($r = 0.51$, $p < .001$). AIsem2 was significantly associated with Final1 ($r = 0.31$, $p < .01$). Correlations between AIsem1 and second-semester outcomes (Midterm2, Final2), and between AIsem2 and second-semester outcomes, were non-significant. These findings indicate that engagement with AI-assisted learning tools is associated with higher exam scores, with associations more pronounced in semester 1 than in semester 2. These results provide partial support for H1.

Table 2. Intercorrelation Matrix: AI Scores and Examination Results

	AIscore1	Midterm1	Final1	AIscore2	Midterm2	Final2
AIscore1	1					
Midterm1	.25*	1				
Final1	.33**	.40**	1			
AIscore2	.51**	.16	.31**	1		
Midterm2	.10	.29**	.35**	-.03	1	
Final2	.05	.22*	.44**	.01	.42**	1

* $p < .05$ (2-tailed), ** $p < .01$ (2-tailed).

Inspection of the full intercorrelation matrix (Table 3) reveals three notable patterns. First, weak to moderate positive correlations ($r = .22-.51$) were observed between AI scores and academic performance indicators across both semesters. Second, the two grit facets were weakly and non-significantly correlated ($r = .16$), and each correlated strongly with total Grit ($r = .64-.66$), confirming them as distinct constructs (Guo et al., 2019). Third, grit (especially Perseverance of Effort) was significantly associated with three HEXACO factors — Conscientiousness, Openness to Experience, and Extraversion ($r = .20-.41$) — and all HEXACO factors were intercorrelated at low to moderate levels ($r = .18-.59$).

H2: Sex as a Moderator of the AI–Performance Relationship

Before testing moderation, we examined baseline differences between male and female students. Independent-samples *t*-tests revealed no statistically significant sex differences in AI tool engagement during semester 1, $t(102) = -0.68$, $p = .50$, or semester 2, $t(102) = 0.65$, $p = .52$. Similarly, no significant differences were found in personality traits, including Grit, $t(102) = -0.68$, $p = .50$, or Conscientiousness, $t(102) = 0.15$, $p = .88$. Examination scores were also comparable across sexes. In semester 1, female students had a mean midterm score of 17.1 (SD = 5.4) and a mean final score of 23.3 (SD = 11.0); male students had a mean midterm score of 17.5 (SD = 4.8) and a mean final score of 26.2 (SD = 11.3). In semester 2, female students had a mean midterm score of 18.1 (SD = 4.3) and a mean final score of 31.3 (SD = 7.8); male students had a mean midterm score of 19.5 (SD = 4.1) and a mean final score of 31.8 (SD = 7.3).

To formally test H2, standardized improvement scores (change in *z*-scores from midterm to final) were computed within each semester to enable valid cross-exam comparison given the differing score scales (Midterm 1: 0–28.2; Final 1: 0–48; Midterm 2: 7–29; Final 2: 11–45). No significant sex differences in standardized improvement were found in either semester 1, $t(35.39) = -0.91$, $p = .368$, or semester 2, $t(31.28) = 0.74$, $p = .467$. Exploratory analysis revealed some variation in improvement patterns when sex and academic department were considered jointly (Table 4).

Table 3. Full Intercorrelation Matrix presenting all Study Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Midterm1	—														
2. Final1	0.40***	—													
3. AIsem1	0.25*	0.33***	—												
4. Midterm2	0.29**	0.35***	0.10	—											
5. Final2	0.22*	0.44***	0.05	0.42***	—										
6. AIsem2	0.16	0.31**	0.51***	-0.03	0.00	—									
7. Grit	0.09	0.19	0.06	-0.06	-0.02	0.16	—								
8. Grit_per	0.19	0.18	0.05	0.18	0.02	0.17	0.66***	—							
9. Grit_con	-0.05	0.08	0.03	-0.25*	-0.05	0.05	0.64***	0.16	—						
10. Hexaco_HH	-0.08	0.09	0.06	-0.17	-0.11	0.14	0.12	-0.05	0.21*	—					
11. Hexaco_Em	-0.16	0.01	0.06	-0.15	-0.01	0.15	-0.16	-0.06	-0.14	0.46**	—				
12. Hexaco_Ag	-0.08	0.06	0.08	-0.09	-0.08	-0.04	0.04	-0.01	0.07	0.48**	0.32**	—			
13. Hexaco_Co	0.02	0.16	0.09	-0.10	-0.06	0.21*	0.41***	0.23**	0.30**	0.59**	0.35**	0.43**	—		
14. Hexaco_OE	0.05	0.10	0.02	0.00	-0.15	0.04	0.16	0.25**	-0.05	0.40**	0.26**	0.37**	0.50**	—	
15. Hexaco_Ex	-0.18	-0.08	-0.06	-0.10	-0.03	0.05	0.23**	0.20*	0.10	0.29**	0.18*	0.27**	0.51**	0.32**	—

* $p < .05$, ** $p < .01$, *** $p < .001$. Note: AIsem1= AI score for first semester, AIsem2= AI score for second semester, Grit= Grit_per= Perseverance of effort, Grit_con= Consistency of Interest, HEXACO_HH= Honesty-Humility, HEXACO_Em= Emotionality, HEXACO_Ag= Agreeableness, HEXACO_Co= Conscientiousness, HEXACO_OE= Openness to Experience, HEXACO_Ex= Extraversion.

Table 4. Standardized Improvement Scores by Sex and Academic Department

Sex	Department	n	Semester 1 Improvement (z)	Semester 2 Improvement (z)
Female	HTM	33	-0.26	-0.04
Female	GTM	28	-0.21	0.02
Female	Finance	21	0.51	0.20
Male	HTM	5	-0.65	-0.93
Male	GTM	7	0.76	0.56
Male	Finance	10	0.19	-0.28

Note: HTM = Hospitality; GTM = General Management

Primary regression: AI engagement predicting improvement, controlling for sex. For semester 1, the regression model was non-significant, $F(4, 99) = 1.95$, $p = .109$, $R^2 = .073$. After controlling for sex, AI tool engagement remained a non-significant predictor of improvement, $B = 0.005$, $p = .821$. Academic department was the only significant predictor, $B = 0.336$, $p = .017$; sex was not a significant covariate, $B = 0.092$, $p = .728$. For semester 2, the model was also non-significant, $F(4, 99) = 0.41$, $p = .800$, $R^2 = .016$, with AI engagement ($B = -0.005$, $p = .823$) and sex ($B = -0.257$, $p = .349$) both non-significant.

Moderation analysis: Sex as moderator. For semester 1, the moderation model including the AI $\times$ Sex interaction term was non-significant, $F(5, 98) = 1.86$, $p = .109$, with a non-significant interaction term ($B = 0.098$, $p = .231$). For semester 2, the moderation model was similarly non-significant, $F(5, 98) = 0.81$, $p = .547$, with a non-significant interaction ($B = -0.082$, $p = .127$). These results support H2: sex did not significantly moderate the relationship between AI tool engagement and academic improvement.

Three-way interaction: Sex $\times$ Grit $\times$ AI tool engagement. A comprehensive three-way interaction model was estimated to test whether the moderating the grit-by-AI interaction differed by sex. The overall model was statistically significant, $F(9, 91) = 2.13$, $p = .034$, $R^2 = .174$ (Adjusted $R^2 = .093$). However, the three-way interaction term was not statistically significant, $B = -0.093$, $p = .590$, indicating that the extent to which the AI-improvement relationship varies by grit does not differ between male and female students.

H3: Prior Academic Standing and AI Tool Engagement

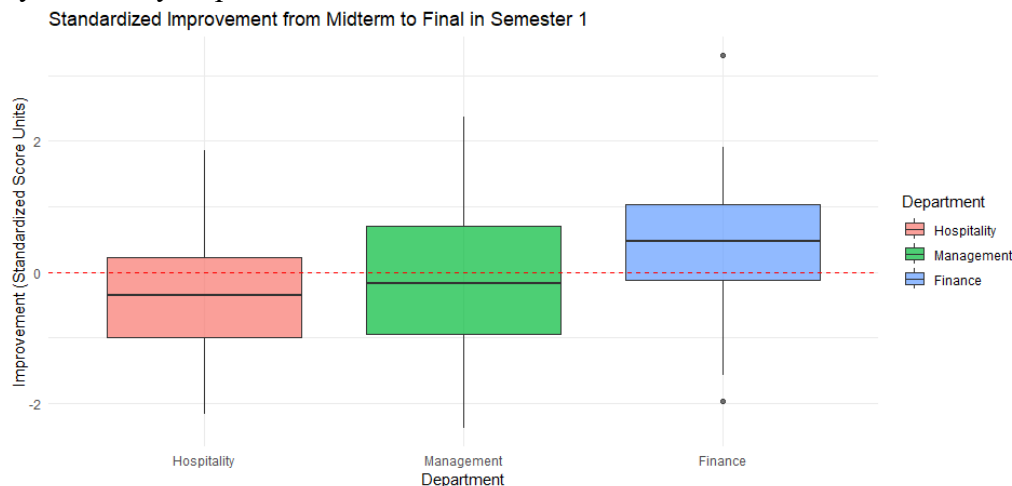
Given that the midterm (worth 30% of the final assessment) and final examinations (worth 50% of the final assessment) were scored on different scales (Midterm 1: 0-28.2; Final 1: 0-48; Midterm 2: 7-29; Final 2: 11-45), raw score comparisons of

improvement were not statistically appropriate. To enable a valid analysis of performance change, student scores were standardized within each examination (converted to z-scores). This transformation allows for the interpretation of improvement as a change in a student's relative standing within the cohort. Additionally, scores were converted to Percentage of Maximum Possible (POMP) scores, and percentile ranks as robustness checks.

Initial analysis revealed no statistically meaningful cohort-level mean improvement in either semester, as expected given that the standardization procedure produces a distribution with a mean of zero by construction. The meaningful comparisons, therefore, lie in the between-group and individual-level variation in improvement. Notably, Figure 1 shows considerable variation in improvement patterns across academic departments.

A one-way ANOVA confirmed that department was a significant predictor of semester 1 improvement, $F(2, 101) = 3.88$, $p = .02$, $\omega^2 = .05$, 95% CI: 0.00-0.15. Post-hoc comparisons indicated that students in the Finance department showed greater improvement than those in the Hospitality and General Management departments, consistent with H3.

Figure 1. Standardized Improvement (Final exam z-score minus midterm z-score) by University Department in Semester 1



Note: A positive value indicates improvement in relative standing.

To test H3 more formally, two hierarchical linear regression models were constructed with standardized improvement as the outcome and AI engagement score, university department, and course repetition status as predictors. For semester 1, the overall model was marginally non-significant, $F(3, 100) = 2.58$, $p = .058$, $R^2 = .072$. AI engagement was not a significant predictor of improvement, $B = 0.005$, $p = .812$. Department was the only significant predictor, $B = 0.343$, $p = .013$. For semester 2, the model was non-significant, $F(3, 100) = 0.25$, $p = .859$, $R^2 = .008$, with AI engagement non-significant, $B = -0.001$, $p = .954$. Students in the Finance department showed greater standardized improvement in semester 1, but AI engagement was not significantly associated with improvement, and this pattern did not replicate in Semester 2.

H4: Moderating Role of Grit

To test H4, we examined whether grit moderated the association between AI tool engagement improvement. A moderation analysis was conducted using the PROCESS macro (Model 1; Hayes, 2012) for semester 1 data, with standardized improvement as the outcome and the interaction term between AIsem1 and grit as the primary predictor, controlling for department and repetition status. Table 5a and b present the full regression and moderation results.

Table 5a. Moderation of the AI Engagement–Improvement association by Grit, semester 1 (N = 101)

Predictor	Model 1: Difference score			Model 2: Residualized change		
	<i>B</i> (<i>SE</i>)	95% CI	<i>p</i>	<i>B</i> (<i>SE</i>)	95% CI	<i>p</i>
Constant	0.43 (0.19)	[0.06, 0.80]	.025	3.81 (1.30)	[1.23, 6.39]	.004
AI engagement	0.02 (0.02)	[−0.03, 0.07]	.382	0.37 (0.16)	[0.06, 0.68]	.021
Grit	0.23 (0.19)	[−0.15, 0.61]	.237	2.57 (1.33)	[−0.08, 5.22]	.057
AI engagement × Grit	−0.13 (0.04)	[−0.21, −0.05]	.003	−0.57 (0.29)	[−1.15, 0.00]	.050
Department: GTM	−0.36 (0.26)	[−0.88, 0.15]	.165	−2.99 (1.81)	[−6.57, 0.60]	.101
Department: HTM	−0.83 (0.27)	[−1.37, −0.28]	.003	−8.01 (1.90)	[−11.77, −4.25]	< .001
Repeating the course	0.27 (0.34)	[−0.42, 0.95]	.437	2.15 (2.39)	[−2.60, 6.89]	.371
<i>R</i> ²	.159			.252		
Model <i>F</i> (6, 94)	2.96		.011	5.29		< .001
ΔR^2 (interaction)	.085		.003	.031		.050

Note. Model 1 outcome: standardized improvement (Final z-score minus Midterm 1 z-score). Model 2 outcome: residualized change (Final regressed on Midterm1). AI engagement and Grit were mean-centered. Finance is the reference category for department. GTM = General Management; HTM = Hospitality.

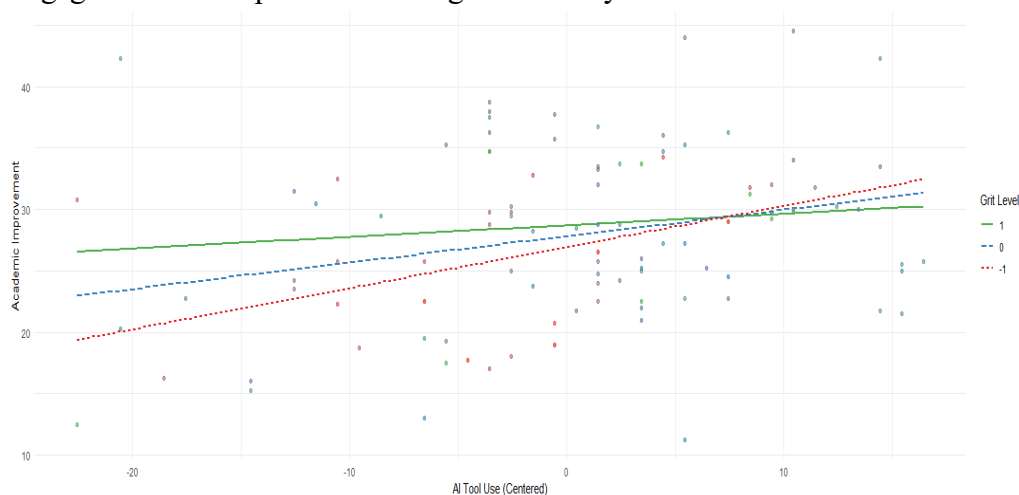
Table 5b. Conditional Associations Between AI Engagement and Improvement at Selected Levels of Grit, Semester 1

Grit level (centered value)	Model 1: Difference score			Model 2: Residualized change		
	<i>B</i> (<i>SE</i>)	95% CI	<i>p</i>	<i>B</i> (<i>SE</i>)	95% CI	<i>p</i>
Low (16th percentile)	0.08 (0.03)	[0.02, 0.15]	.015	0.64 (0.23)	[0.19, 1.09]	.006
Median (50th percentile)	0.03 (0.02)	[−0.02, 0.07]	.240	0.40 (0.16)	[0.08, 0.72]	.014
High (84th percentile)	−0.06 (0.03)	[−0.12, 0.00]	.063	0.02 (0.21)	[−0.41, 0.44]	.931

Note. Values are the association between AI engagement and improvement at the stated Grit percentile, from the models in Table 5. Models were estimated with the PROCESS macro.

The moderation model was statistically significant, $F(6, 94) = 2.96$, $p = .011$, $R^2 = .159$ (Adjusted $R^2 = .113$). At average Grit, AI tool engagement was not significantly associated with improvement, $B = 0.02$, $SE = 0.02$, $p = .382$, and Grit was not significantly associated with improvement at average AI engagement, $B = 0.23$, $SE = 0.19$, $p = .237$. The $AI \times Grit$ interaction was significant and negative, $B = -0.13$, $SE = 0.04$, $p = .003$, 95% CI $[-0.21, -0.05]$, $\Delta R^2 = .085$. Conditional associations were examined at the 16th, 50th, and 84th percentiles of Grit. Among students with lower Grit, higher AI engagement was associated with greater improvement, $B = 0.08$, $SE = 0.03$, $p = .015$; the association was non-significant at median Grit, $B = 0.03$, $p = .240$, and at higher Grit, $B = -0.06$, $p = .063$. This pattern is consistent with a compensatory association, in which AI engagement is related to improvement mainly among less gritty students. Because the design is observational and improvement scores are susceptible to regression to the mean, the pattern should not be interpreted causally. A robustness analysis using residualized change scores showed the same direction of interaction, though it was weaker ($B = -0.57$, $p = .050$). The simple slopes plot is depicted in Figure 2.

Figure 2. The Moderating Effect of Grit on the Relationship between AI Tool use and Academic Improvement in Semester 1. The Positive Association between AI Engagement and Improvement is Significant only for Students Low in Grit.



Discussion

The existing literature (Johnson et al., 2009; Cano & Troya, 2023) suggests that the use of AI tools can enhance students' engagement and academic performance. In the present study, this finding was observed in the first semester (Financial Accounting) but was not replicated in the second semester (Management Accounting). This discrepancy may indicate that the novelty effect of the AI tool diminished over time, or that students perceived the effort required for engagement as insufficiently rewarded in terms of grade improvement. No significant difference was noted among students repeating the course. In agreement with Zhang and Zhao (2022), we found that engagement with AI-assisted learning tools is associated with improved academic

performance, with more pronounced effects in Financial Accounting than in Management Accounting.

In agreement with Fachrurrozie et al. (2025), we found no moderating effect of sex on the relationship between AI teaching tool use and academic performance. A particularly notable finding, contrasting with Weeks et al. (2024), whose study involved generative AI tools such as ChatGPT, reveals that students with higher prior academic standing (i.e., Finance department students) experienced significantly greater improvement in academic performance in semester 1, but not in semester 2, when utilizing the AI teaching tool relative to students with lower prior academic standing (i.e., Hospitality students).

Finally, a central contribution of this study is the finding that students with lower grit, specifically, lower perseverance of effort, demonstrated significantly greater academic improvement when engaging with the AI teaching tool compared to their higher-grit counterparts. A plausible explanation for this finding is that low-grit students, who typically struggle to sustain effort independently, may have been associated with greater improvement when engaging with the structured scaffolding, adaptive feedback, and repeated practice opportunities that the AI platform provided. These features may have effectively compensated for lower intrinsic perseverance. High-grit students, by contrast, may already possess sufficient self-regulatory resources to perform well irrespective of the AI tool, reducing the incremental benefit they derive from it.

Conclusions, Policy Implications and study Limitations

The results of this study suggest that AI teaching tools in undergraduate accounting can differentially benefit students based on individual characteristics. Although no direct, overall effect of AI engagement on academic improvement was observed across the full cohort, significant moderation effects emerged: AI tool engagement benefited students with lower grit in semester 1, and students in higher-standing academic departments demonstrated greater improvement when engaging with AI tools in semester 1.

These findings carry policy implications for accounting educators and platform developers. AI teaching tools should be positioned as a targeted support resource, particularly for students who may struggle with sustained independent effort, rather than as a uniformly beneficial supplement. Platform design should foreground adaptive scaffolding, structured practice, and immediate corrective feedback, as these are the features most likely to benefit students with lower perseverance.

A primary limitation of this study is the relatively small analytic sample ($N = 104$), which necessitates replication with larger cohorts to validate the findings. Despite this constraint, the conclusions rest on actual performance data rather than self-reported perceptions, and participation criteria were stringent: students were enrolled in both subjects, completed the grit and personality instruments, and consented to use of their academic records. Steps were taken to address data quality concerns: Cronbach's α was calculated for all scales, respondents whose answers substantially lowered reliability were excluded, and patterned responses were

identified and removed. The grit scale was administered in class, with submission required before students left the room, mitigating the risk of outsourced or disengaged responding.

A further limitation is the use of department of enrollment as a proxy for prior academic achievement rather than actual entrance scores. While the directional ordering of departmental academic standing (Finance > Management > Hospitality) is consistent with university admission standards, future research should incorporate objective entrance score data to test H3 more directly. The limited temporal scope (one academic year) and geographic specificity of the research may also affect generalizability. This study is therefore explicitly exploratory, and replication with larger, more diverse samples is strongly encouraged.

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Declaration of interest statement: There are no competing interests to declare

Ethics Committee Approval: The National Bioethics Committee approved the study and instrument used, approval number No. EP2025-01-60.

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