AI Teaching Tools Create Dynamic Scaffoldings rather than Static Staircases for Accounting Students

The primary objective of this paper is to investigate whether AI teaching tools in undergraduate accounting subjects lead to improved academic performance. The authors have also investigated whether there is any correlation or relationship between gender or the students' overall academic merit and the use of the AI teaching tools. Unlike other researchers, the current authors have also used the personality grit (i.e., a non-cognitive trait based on a person's perseverance of effort, taking into consideration their passion to achieve long-term goals) completed by each student in an effort to identify if that has an impact or a correlation on the use of AI teaching tools and the final mark achieved. Having studied the actual use of AI teaching tools for Financial and Management Accounting, and the students' individual responses to the personality grit, as well as their gender, overall final marks, and academic performance, it was found that students who had lower personality grit when using AI teaching tools achieved significantly higher marks than students with higher grit. It was also found that students with overall higher entrance academic scores when using the AI teaching tools achieved significantly higher final marks than students with lower university entrance scores. No relationship was found relating to gender. This has enabled the researchers to prove that when AI is integrated into teaching and assessment, a dynamic scaffolding rather than a static staircase is developed.

Keywords: *AI teaching tools, personality grit, academic performance*

Introduction

The primary aim of the paper is to determine whether AI teaching tools used in undergraduate accounting improve students' academic performance in the subject. The reason this is important to investigate is that students' engagement and interest in accounting courses and the profession have fallen (Malik et al., 2025). Thus, the findings are important to the accounting discipline in Higher Education, as they address the 'accounting pipeline'.

The World Economic Forum (2024), cognizant of the fact that technology is accelerating at an unprecedented speed, has acknowledged that education needs to recognize new opportunities and risks and navigate towards an education system that better prepares its students for the future. The same report highlighted that Artificial Intelligence (AI) holds immense potential to "revolutionize teaching methodologies, personalize learning experiences, and streamline administrative processes" (p.3). Thus, it recommends that AI should not replace the role of the teacher but rather enhance it by empowering educators to understand student needs better and foster motivation. Thus, the World Economic Forum (2024, p.4) suggests that educators ought to utilize AI to help students achieve better outcomes in technology skills and facilitate, through their teaching, global citizenship, innovation, technology, and interpersonal skills. It is also suggested in the same report that learning experiences ought to be personalized, self-paced, accessible, problem-based, and based on student-driven learning. Thus, a pedagogical shift is suggested to move away from the traditional teaching of a static staircase to an AI-integrated dynamic scaffolding.

Over the years, researchers (Holmes et al., 2019; Holmes & Douglass, 2022; Dawkins, 2023; Dennis, 2023) have commented on the 'accounting student pipeline', the weak current state of accounting education, plus perceptions that accounting is a difficult subject. Boyce (2018, 377-379) has documented the meaningful development and reform needs of accounting education, which have remained unchanged for more than 50 years. Sundem (2014) has found that some progress was made in the 1990s and 2000s, but that was isolated to specific universities, thus allowing the 'crisis in accounting education' to persist (Gabbin, 2002). Hence, a pressing need for accounting education is to meet the needs of society, the profession (Zamaina & Subramanian, 2024), as well as the changing times (Almutiry et al. 2022). As Ballantine et al. (2024) assert, the purpose of higher education to help create critical and creative individuals has been neglected. Educators need to "focus on both technical accounting skills, as part of vocational or professional skill formation and a student-centered humanistic and formative approach to individual development" (p.2). Utilizing AI and making accounting education more engaging and relevant will force educators to enhance the skills and reflexivity required to understand accounting. Thus, as some authors argue (Boyce et al., 2001; Dillard & Vinnari, 2017; Douglas & Gammie, 2019; Ballantine et al., 2024), accounting graduates will need to possess more soft skills, critical as well as judgment skills, and a critical understanding of accounting.

Therefore, accounting educators need to address the accounting pipeline by incorporating and aligning technology skills with learning objectives in the accounting curriculum to meet changing business demands (Akbulaev et al., 2021; Vachkova et al., 2022) and enable students to engage holistically in the learning process (Xiao & Foster, 2022).

This research is original because it has studied the students' performance in the introductory subjects of Financial and Management Accounting. Both subjects are compulsory for first-year students in three different majors (Finance, Management, Hospitality) at the public universities of the country investigated. The students' personality grit was then compared to their individual engagement with the AI teaching tool and to their final mark for each subject. Thus, unlike other researchers (Djatej et al., 2015; Jackling & Calero, 2006; Sadri & Robertson, 1993) who measured factors influencing interest in accounting, or perceptions about the accounting profession (Djatej et al., 2015; Jackling & Calero, 2006; Karlsson & Noela, 2021; Tan & Laswad, 2006), or beliefs about post-graduate employability (Awadallah Elgharbawy, 2020; Kim et al., 2002; Samsuri et al., 2016) this paper is an original contribution to knowledge as it has surveyed student engagement, performance and their personality grit in an effort to establish if dynamic scaffolding can be created to address the above issues.

The paper is organized as follows: Section two of the paper will cover the literature review, starting with the theoretical models used to contextualize the study in question, and then moving on to discuss the evolution of education, the pedagogical skill development through AI teaching tools, the use of AI in education, and finally, the use of AI in accounting education. This is followed by the discussion of the four hypotheses developed, which will contribute towards answering the research question. The next section discusses the methodology used, followed by the results and the discussion of the findings. Finally, we conclude with a discussion of the contributions, limitations, and future directions of our research

Literature Review

Theoretical Framework

The integration of AI teaching tools in tertiary education could substantially transform the landscape of learning experiences, providing unique opportunities to understand and enhance non-cognitive skills such as grit and personality factors (Arpaci et al., 2025). A fundamental characteristic of AI systems is their interactive nature. Their use depends importantly on the adaptability of the user. For this reason, a number of studies focus on the relation of the AI tools with personality traits (González-Calatayud et al., 2021; Luo et al., 2025).

Grit, a concept introduced by Duckworth and her colleagues (2007) primarily, measured through a 12-item questionnaire by tapping two dimensions: perseverance of effort and consistency of interest. Grit correlated with academic performance among Ivy League undergraduates, with higher GPAs in college and lower SAT scores (see Isenberg et al., 2020; MacCann et al., 2009). Grit proved to be an important index of academic success and personal growth, as it encourages resilience and sustained engagement in challenging tasks (Duckworth et al., 2007; Eisenberg et al., 2014; Kovacevic et al., 2025; Mittal et al., 2024). At the same time, personality dimensions, especially those outlined in the HEXACO model, include honesty, openness to experience, and emotionality, which influence students' learning behaviors, motivation, and persistence (Jia et al., 2022). Ashton and Lee (2009) designed a self-referenced questionnaire measuring six dimensions: (a) honesty-humility, (b) emotionality, (c)extraversion, (d) agreeableness, (e) conscientiousness, and (f) openness to experience (Ashton & Lee, 2007). AI teaching tools offer unparalleled potential to adapt educational content and methodologies to individual differences, tailoring instruction to align with learners' unique personality profiles and levels of grit. These tools employ adaptive learning algorithms, personalized pathways, and real-time analytics to address the specific needs, strengths, and weaknesses of learners, fostering an environment where persistence and self-discipline can thrive. For instance, research has shown that tailoring teachable agents with personality traits can stimulate deeper engagement and enhance learning outcomes in mathematics education by promoting student motivation and commitment. Moreover, educational systems that leverage AI's ability to analyze student behaviors and dynamically respond to their attitudes and personality further cultivate resilience and academic motivation. Accordingly, the intersection of AI teaching tools, grit, and personality factors serves as a promising frontier in education technology, with the capacity to empower students to overcome challenges, persist in their learning journeys, and enhance their overall academic and personal achievements. However, further empirical exploration is required to clarify the underlying mechanisms of these interactions and optimize AI tools for diverse educational settings.

Bao (2019) argues that AI can take the form of a combination of any or all of the following: student module, teaching module, and evaluation model. The student module is primarily used by students to facilitate autonomous learning and help them grasp the concepts and learning objectives set by the teacher (Biggs, 1999, 2014). In the process, they may also be asked to complete several questions. Thus, students at this stage learn visually and interactively, and as Bao (2019) notes, this process is innovative and taps into the potential of each student. The teaching module relates to technology-assisted tools available to teachers in developing teaching materials, quizzes, and forms of assessment. Evaluation models also collect information about each student's performance and share it with the teacher. Bao (2019) has concluded that the use of AI in teaching accounting courses can make the "presentation of teaching content more suitable for cognitive characteristics of students and enhance students' understanding of and mastery" (335) of the teaching material. The authors of the current paper, having looked at various AI accounting teaching tools, decided that the one that fits Bao's theoretical model, as well as the World Economic Forum's suggestions mentioned earlier, is the McGraw Connect AI teaching tool. Thus, the authors decided to use this tool for two semesters for the first year of Financial and Management Accounting subjects.

Evolution of Education

Holmes and Tuomi (2022, 543) advocated that "the potential of AI for education and learning, and the role of education in developing …AI literacy" is becoming a hot topic. This is due to the massive global investment in AI technology. To illustrate, in 2021 this investment reached 94 billion US dollars (Statista, 2022).

Educators and academics have been aware that students have used essay mills and other 'unorthodox' methods to complete their assigned work. At the same time, AI over the years became a useful tool not only to assist in the teaching process, but it also contributes to a progressive teaching method. Interestingly, many AI systems have been built on 'cognitive teaching' (Holmes & Tuomi, 2022), assuming that the human brain is an information processor.

As Hakim et al. (2021) and Verberg et al. (2020) state, AI tools in education have the potential to decrease administrative time, contribute to teacher support, and stimulate new pedagogical and andragogical approaches. Researchers over the years have looked at the use of AI in developing and marking exams (Choi, et al. 2023); operations management of final exams (Trietsch, 2023), as well as the accuracy of the use of AI in assisting in the education of accounting (Wood et al., 2023). Other researchers (Wood et al., 2023) have evaluated ChatGPT and found that this form of AI enables participants to do better on exams when administered in English. However, Wood et al., (2023) noted that ChatGPT appears to have high risks of error and unreliability because (a) it does not recognize it is performing mathematical operations and makes non sensical errors, (b) it provides descriptive explanations for its answers, even though they may have been incorrect, (c) it makes up answers, and (d) it struggles to answer multiple choice questions. Thus, ChatGPT does not appear to be a reliable tool to be used in AI teaching of accounting subjects as it is not trustworthy; however, students consider it a useful tool because it is easy to use (Sundkvist and Kulset, 2024).

Pedagogical Skill Development through AI teaching tools

Casal-Otero et al. (2023) have studied the age-appropriate pedagogies and have found that AI literacy development provides a more holistic learning environment at higher education levels. AI learning objectives address three dimensions because they focus on students': a) cognitive development by synthesizing understanding of concepts, processes, principles, and applications, (b) psychomotor development, and (c) social and emotional development.

Bao (2019) found that the application of AI in accounting teaching at higher tertiary levels not only optimizes teaching methods but also addresses classroom design, enhances student-teacher interaction, and provides data for teachers to study the students' performance. Furthermore, AI, when used in teaching, can improve the quality and efficiency of financial management professional talents cultivation, reduce human management costs (Qian, 2022), and provide students with the knowledge to adapt to the current economic situation (Cherukuri, et al., 2021).

As noted by the World Economic Forum (2024, 7) by "integrating AI technologies into educational assessment offers the potential for educators to gain real-time, data- driven insights into students' learning trends, identifying areas of strength and weakness and assessing instructional effectiveness on a large scale". Cai (2022) advocates that because accounting and AI are no longer independent of each other, "accounting majors in colleges and universities should inspire students to become front-line application-oriented talents with innovative and entrepreneurial abilities to meet the needs of society and jobs" (p.9). Thus, the same author claims that if universities wish to adhere to a student-oriented approach, finance and accounting educators need to utilise AI in their teaching to meet the demand and supply of enterprises for financial management talents, promote the improvement of enterprises' financial management level, and accounting reform development.

Use of AI in Education

Fitria (2021) has noted that there is a need for creativity and innovation in the learning process, and AI is a useful tool to be used in the teaching and learning process. As Fitria explains, when instructors use AI tools, they can “understand student needs more easily and more deeply” while students can “learn according to their needs without encountering difficulties” (p.135). The instructor’s work in correcting, administering quizzes, homework, exams, explaining concepts, and making administrative reports is made more efficient and effective as they can save energy and focus on non-systemic work to “create a golden generation with more character and quality with natural intelligence where robots cannot” (Fitria, 2021:145)

Zhang and Zhao (2022) have found that by utilizing AI-assisted education, for accounting courses there is an increase in student participation and performance, an improvement in teaching quality and effectiveness, whilst students tend to be more efficient in completing questions as it takes them 30% less time to complete exercises and students have an 80% chance to complete the questions set for homework. The same authors argue that the traditional mode of teaching, by utilizing a textbook and a blackboard alone, is “restricted to the development of information through time and space” (p.1). In addition to the effectiveness and efficiency achieved if students use AI tools in completing accounting exercises it has been found that when students complete their accounting homework “in a 50-minute session contributed to an improvement in test performance of approximately 27 percentage points; in comparison to students using their textbook and course notes to complete the same homework which improved their test Acc by about 8 percentage points” (Johnson et al. 2009: 30)

To promote holistic AI literacy, Dai (2025) agrees with Long and Magerko (2020), who suggest integrating plugged and unplugged activities. Plugged activities (Ng et al 2023) employ technologies such as problem-solving exercises, whereas unplugged activities focus on concepts and thinking skills (Lindner et al. 2019). Recent research highlighted that AI-based teaching tools enhance learning outcomes, but their effectiveness is moderated by key personality and cognitive factors (Luo et al., 2025; Wang et al., 2024). Studies (Arpaci et al., 2025; Shepman et al., 2023) demonstrate that students with higher conscientiousness (e.g., self-discipline) and Grit (particularly Perseverance of Effort) engage more deeply with AI tools, leading to greater academic gains. These traits predict consistent tool usage, which in turn improves performance in structured tasks in accounting. Additionally, emotionality may reduce engagement, as highly anxious students tend to avoid AI interfaces. Cognitive factors such as processing speed and working memory further influence how efficiently students adapt to AI-driven feedback. Interestingly, gender and educational background play roles, with females and students in quantitative fields (e.g., Finance) benefiting disproportionately (Brooks et al., 2025). These findings suggest that AI tools do not operate uniformly; instead, their impact cascades through a network of individual differences, where personality and cognitive strengths shape the trajectory of learning success. Future designs should personalize AI interactions based on these psychometric profiles to maximize efficacy.

Use of AI in accounting education

Zhang and Zhao (2022) have highlighted that the "traditional teaching of financial accounting is complicated due to old-age methods of teaching, simplistic methods of education, and insufficient participation of students" (p.1). These authors have argued that educators ought to increase the students' involvement, enhance the impact of learning, and encourage the quality training of financial accounting talents. These can be achieved through interactive AI teaching tools.

Nikolova (2023) acknowledges that accounting is an evolving discipline as it must keep-up with the needs of society, economy, and business. Thus, accountants need to prepare accounting reports which can be the basis for "(a) forming reliable management decisions, (b) economic forecasts and (c) implementation of efficient control over the economic and financial activity" (p144). In addition to those reasons for using AI in accounting education, Hassan et al. (2021) have found that the use of AI in accounting education indicates technology readiness of students, which in turn will lead to a significant influence on technology adoption.

Nikolova (2023) notes that along with traditional technical accounting knowledge regarding: (a) the accounting system, (b) accounting documentation and document flow, (c) the process of accounting, (d) evaluation and calculation, (e) double accounting recording, and (f) summarization and systematization of accounting information; complex financial and economic knowledge is also required. The same author advocates that accounting students achieve professional success (OECD, 2022) and develop their critical thinking, communication, and problem-solving skills. The first author of the paper, having taught accounting students for the last three decades, realized that student study time and concentration have been reduced as they devote more time to social media rather than studying, an issue also raised by Dennis (2023) in his accounting student pipeline work. As a result, students need an incentive to be engaged in the subject (Lakshmi et al, 2023). This can be achieved using data visualization, which combines analysis and communication (Malik et al, 2025).

Phillips and Graeff (2014) found that accounting students were able to develop deeper learning through a computer-based mechanism accounting simulation. This was possible due to the increased understanding of abstract concepts, which enhanced their confidence in learning the subject knowledge. These findings were more recently supported by Zhang and Zhao (2022). Zhang et al. (2019) studied engineering and accounting students and found that accounting students can gain know-how and knowledge in a short time, when using AI assisted teaching. Thus, creating a 'smart classroom' helps educators meet new challenges and improve student abilities and performance. These tools, as Zhang and Zao argue, enable the development of a 'smart learning system' which helps educators and students work together more effectively by keeping track of each other's progress throughout the lesson; thus, learning becomes more enjoyable for everyone.

Researchers over the years (Freire, 1973; Freire, 1998; Laurillard, 2001) have advocated that higher education teaching ought to move students away from shallow learning to deep learning since knowledge is not enough. By utilizing AI accounting teaching tools, educators are tapping into critical pedagogy, enhancing learning, and providing an opportunity to move away from rote learning, regurgitation, and surface learning.

As Cano and Troya (2023) have found, AI-based systems can provide not only a more accurate and detailed assessment of student performance through the analysis of patterns in the data provided but can also enable the educator to have specific feedback to help students' improvement. In an "era where support and coaching strategies have become established as indicators of quality, these supports streamline and refine the management of the cabinets or centers dedicated to their implementation" (p. 2).

Many studies in educational psychology have found that even the best-designed intelligent AI systems do not lead to superior student performance when compared to situations where students use a textbook to solve problems or answer questions during training (Chi, et al. 2001; Evens & Michael 2006; Katz, Connelly, & Allbritton 2003; Reif & Scott 1999). At the same time, research (Blayney and Freeman, 2008 and Goldwater and Fogarty 2007) has found that AI can be used to "algorithmically generate limitless sets of numerical problems and cases on which students can work and be assessed" (Johnson et al., 2009:32), thus further testing is required. Such systems respond to the student's individual needs; thus, it is not a set of "canned instructions" (Johnson et al. 2009:31). Furthermore, Johnson et al. (2009: 31) in reviewing the literature on AI used in Accounting education have classified AI based systems as " part of a category of educational technology that also includes computer-assisted instruction (Handy 2005), computer-based learning (Halabi 2006; Halabi, Tuovinen, & Farley 2005), computer assisted learning (McDowall and Jackling, 2006) and even hypertext linking (Crandall and Phillips 2002)".

The semi-systemic review of the literature undertaken by Tandiano (2023) confirmed that the bulk of publications relating to AI and its impact on accounting education are limited. The same is confirmed by Ballatine et al. (2024), who argue that accounting educators need to ensure their teaching meets the needs of contemporary society since accounting is a difficult subject to pass and not a subject that creates critical and creative individuals, thus this paper will endeavour to address the gap existing in literature.

Methodology

Research Objectives

The aim of the paper is to investigate if the use of AI teaching tools in undergraduate accounting subjects contributes toward a higher final mark for the students, given a student's personality grit on perseverance of effort thus creating a dynamic scaffolding being created rather than a static staircase.

To answer the above research questions four hypotheses have been developed following the literature review.

HI: Academic performance in accounting subjects improves when using AI teaching tools

Zhang and Zhao (2022) have found that by utilizing AI-assisted education, for accounting courses there is an increase in student participation and performance. Thus, this research will test if this applies to both Financial and Management Accounting subjects when using the same population.

H2 Gender has a moderating effect on subject performance using AI teaching Tools

Fachrurrozie et al. (2025) have found that the gender variable can influence the intention to use AI tools, however there was no moderating effect found between gender and performance. Lu & Chiou, (2010) found that male teachers tend to be more satisfied of online platform studies than female teachers. In addition, it has been found that there are perceptions that males consider the AI tools to be more useful and easier to use, than females (Bajaj et al., 2021). However, there have been no concrete findings regarding gender as a moderating effect on academic performance having used AI teaching tools in accounting.

H3 There is a relationship between academic merit and the use of AI teaching tools and academic performance

Researchers (Wecks et al., 2024) have found that the learning progress of students with high learning potential will be harmful if they use AI tools. However, this finding does not relate to students registered in accounting subjects but relates to the impact of students' usage of generative artificial intelligence (GenAI) tools such as ChatGPT on the students' exam performance. However, there is no finding relating to a plugged and unplugged activities that will contribute to a holistic AI literacy (Dai, 2025).

H4 Personality factors mediate the relationship between AI tool usage and student academic performance

Fachrurrozie et al. (2025) advocated that AI tools may offer benefits for learning and engagement, particularly to students with lower academic outcomes, however they have not used any cognitive or personality grit testing to determine the correlation between perseverance and academic performance.

Materials and Methods

In the academic year 2024-2025 for the Financial and Management Accounting subjects, which run over two consecutive semesters, the researchers utilize a textbook published by McGraw which provided AI teaching tools. The tools provided by the publisher can be classified as holistic AI literacy (see Dai, 2025 framework) and fulfilled Bao's (2019) theoretical model. The AI tools were both plugged and unplugged (Long and Magerko, 2020; Ng et al 2023; Lindner et al. 2019). As suggested by researchers (Christoper, 1996; Biggs,1999, 2014) teachers ought to initially identify the learning objectives, then the AI tools will design assessments that will motivate and encourage students to be engaged in the subject, an argument also put forward by (Ali et al. 2024). The first author, an accounting professor, identified the learning objectives for each chapter, and the AI educational tools provided a list of questions for each student to complete. If students, when completing the questions, did not get the correct answer, the system would divert the student to the section of the book that related to the question so he/she can do further reading before attempting to answer the question again. Students could have up to three attempts to complete the question and resubmit. The system would mark each weekly assessment and determine the internal assessment (20% of the final mark). It would also identify which learning objectives the instructor needed to revisit based on the students' weekly performance. The system would also generate the midterm (30% of the final mark) and final exam (50% of the final mark) based on the parameters set by the instructor and develop quizzes for students to practice on the same basis as the midterm and final exam.

The AI teaching tool used enabled students to have a personalized interactive system, which enabled the creation of an intelligent system capable of learning, reasoning, adapting, and performing tasks, like humans. The information created was stored, analyzed, evaluated and communicated to the instructor to enable him/her to adapt teaching materials. Additionally, this tool navigated the engagement of students and ensured students completed the exercises within the set timeframes as no extensions could have been granted on an individual basis thus, encouraged the students to complete tasks timely without procrastination.

All students who registered for the accounting subjects were asked to register on the AI teaching tool. At the same time, ethical clearance from the National Bioethics Committee was sought in February 2025 to enable the current authors to use the personality grit and the students' individual academic performance for the subjects of Financial Accounting and Management Accounting. Both courses are first-year compulsory courses offered in two consecutive semesters for three departments: Finance, Management, and Hospitality. It is worth noting that the entrance scores to those departments vary. Better academic performance students register in the Finance Department, then in Management, and finally in the Hospitality and Tourism Department. Some students were repeating either subject.

Given that the relevant literature shows a significant relation between personality factors and academic performance, it was decided to administer a personality test, the HEXACO personality inventory (Lee & Ashton, 2004), to test whether personality factors mediated or moderated the effects of AI-based assessment tool on academic performance. In this vein, we decided to additionally administer the Grit scale (Duckworth et al., 2007), because recent research identifies Grit as a more fine-grained measure of Conscientiousness, increasing the predictive usefulness of this personality factor (Eisenberg et al., 2014; Isenberg et al., 2020; MacCann et al., 2009).

Results

An Exploratory Factor Analysis (EFA) was conducted on the 12-item Grit Scale using Maximum Likelihood (ML) estimation and a promax (oblique) rotation. The suitability of the data for factor analysis was confirmed. The scree plot and model fit statistics supported a two-factor solution, which aligns with the theoretical conception of grit comprising two related but distinct facets. The two-factor solution accounted for 40% of the total variance in the items. The factors were moderately correlated ($r = -0.24$), indicating they measure distinct but related constructs. The pattern matrix of factor loadings revealed a clear, simple structure. Items intended to measure "Consistency of Interests" loaded saliently on the first factor, while items intended to measure "Perseverance of Effort" loaded saliently on the second factor. One item (item11) demonstrated a complex structure, cross-loading on both factors, though more strongly on "Consistency of Interests". Model fit indices suggested the two-factor model provided adequate to good fit to the data. The Root Mean Square Error of Approximation (RMSEA) was 0.048 (90% CI [0.00, 0.08]), and the Tucker-Lewis Index (TLI) was 0.945. The reliability of the factor scores was high, with correlation between scores and factors of 0.91 for both factors.

A second EFA was subsequently performed on the 60-item HEXACO personality inventory using ML estimation and a promax rotation to test its hypothesized six-factor structure. The analysis yielded six factors that collectively accounted for 29% of the total variance. The correlation matrix revealed generally low to moderate inter-factor correlations, ranging from |0.02| to 0.22, supporting the relative independence of the derived factors. The pattern of factor loadings (see Table 2) provided mixed support for the theoretical structure. While several factors captured their intended constructs, the solution was characterized by a significant number of items with weak, complex, or unexpected loadings. For instance, the first factor was defined by strong loadings from items such as item 53 and item 35, while the second factor was marked by items like 4 and 52. However, many items failed to load saliently on any factor, resulting in low communalities and suggesting a poor fit for the six-factor model in this sample. This interpretation is supported by the model fit indices. The TLI of 0.592 falls below conventional thresholds for acceptable fit, indicating that the six-factor model does not adequately reproduce the observed correlation matrix. However, the RMSEA of 0.048 (90% CI [0.042, 0.054]) suggests a reasonable error of approximation. Despite the overall poor model fit, the reliability of the derived factor scores was acceptable, with correlations between scores and factors ranging from 0.89 to 0.92. Based on the two EFAs, we estimated the two factors of the Grit scale and the six factors of the HEXACO inventory.

To assess how AI-assisted educational tools influence student outcomes in accounting classes, we performed various statistical analyses using SPSS (Version 28). Preliminary analysis showed that the skewness and kurtosis of all variables ranged between ±2. At first, we calculated the intercorrelation matrices between AI-assisted educational tools (AI scores) and academic achievement (Midterm and Final exam scores). We also examined the relationships between academic performance, the two Grit subscales, and the six HEXACO factors.

Hypothesis 1: Relationship Between AI Tool Use and Academic Performance.

Concerning the relation of AI tool usage with academic performance, we estimated the intercorrelation matrix between AI scores (Aiscore1 and AIscore2) and exam results (Midterm1, Final1, Midterm2, Final2). The results (Table 1) revealed significant positive correlations between these variables. Specifically, AIscore1 was moderately correlated with Midterm1 ($r = 0.25$, $p < 0.05$) and Final1 ($r = 0.33$, $p < .01$). AIscore1 showed a stronger association with AIscore2 ($r = 0.51$, $p < .01$) but non-significant correlations with Midterm2 and Final2. In addition, a significant correlation was revealed between AIscore2 and Final1 ($r = 0.31$, $p < .01$). These findings suggest that engagement with AI-assisted learning tools is associated with improved academic performance, with more pronounced effects in the first semester (i.e. when Financial Accounting was taught).

Table 1. The intercorrelation matrix between AI scores and exam 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).

The intercorrelation matrix examining academic performance, Grit subscales, and HEXACO factors revealed only three statistically significant associations. Specifically, Midterm scores exhibited a weak correlation with both Grit subscales ($r = 0.18$, $p < 0.01$ for Perseverance of Effort and $r = -0.16$, $p < 0.05$ for Consistency of Interest) and the HEXACO Emotionality factor ($r = -0.15$, $p < .05$).

Hypothesis 2: Gender is a moderating effect on subject performance using AI teaching Tools

Before testing our primary hypotheses, we examined whether male and female students differed on key baseline variables. The sample comprised 99 female students (73.9%) and 35 male students (26.1%). Independent samples t-tests revealed no statistically significant sex differences in AI tool engagement during Semester 1 [$t(57.11) = -0.91$, $p = .365$), or Semester 2, $t(37.79) = 0.71$, $p = .484$)]. Similarly, no significant differences were found in personality traits, including Grit [$t(63.29) = -0.91$, $p = .365$) and conscientiousness, $t(59.90) = 1.34$, $p = .185$)].

Analysis of academic performance showed comparable midterm and final exam scores between sexes across both semesters. In Semester 1 (Financial Accounting), female students had a mean midterm score of 17.1 ($SD = 5.4$) and a mean final score of 23.3 ($SD = 11.0$), while 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 (Management Accounting), female students had a mean midterm score of 18.1 ($SD = 4.3$) and a mean final score of 31.3 ($SD = 7.8$), while male students had a mean midterm score of 19.5 ($SD = 4.1$) and a mean final score of 31.8 ($SD = 7.3$).

When examining standardized improvement scores (change in z-scores from midterm to final), no significant sex differences emerged in either Semester 1, $t(35.39) = -0.91$, $p = .368$), or Semester 2 $t(31.28) = 0.74$, $p = .467$). However, exploratory analysis revealed notable variation in improvement patterns when considering the interaction between sex and academic department (see Table 2).

Table 2. 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 Analysis: AI Tool Use and Academic Improvement Controlling for Sex: We next tested our primary hypothesis that AI tool use would predict academic improvement, while controlling for sex, academic department, and course repetition status. For Semester 1, the regression model was not statistically significant, $F(4, 99) = 1.95$, $p = .109$, and accounted for 7.3% of the variance in improvement ($R^2 = .073$). After controlling for sex, AI tool engagement remained a non-significant predictor of improvement ($\beta = 0.005$, $p = .821$). The academic department was the only significant predictor in the model ($\beta = 0.336$, $p = .017$), while sex was not a significant covariate ($\beta = 0.092$, $p = .728$).

For Management Accounting (i.e. semester 2), the regression model was also non-significant, $F(4, 99) = 0.41$, $p = .800$, accounting for only 1.6% of the variance ($R^2 = .016$). AI tool engagement remained non-significant ($\beta = -0.005$, $p = .823$), as did sex ($\beta = -0.257$, $p = .349$) and all other predictors. A model comparison using ANOVA confirmed that adding sex to the baseline model (which included AI tool use, department, and repetition status) did not significantly improve model fit for Semester 1, $F(1, 99) = 0.12$, $p = .728$.

Moderation Analysis: Testing Sex as a Moderator: We tested whether sex moderated the relationship between AI tool use and academic improvement. For Semester 1, the moderation model including the AI tool use × sex interaction term was not statistically significant, $F(5, 98) = 1.86$, $p = .109$. The interaction between AI tool use and sex was non-significant ($\beta = 0.098$, $p = .231$), indicating that the relationship between AI tool engagement and improvement did not differ significantly between male and female students. Similarly, for Semester 2, the moderation model was non-significant, $F(5, 98) = 0.81$, $p = .547$, with a non-significant AI tool use × sex interaction ($\beta = -0.082$, $p = .127$).

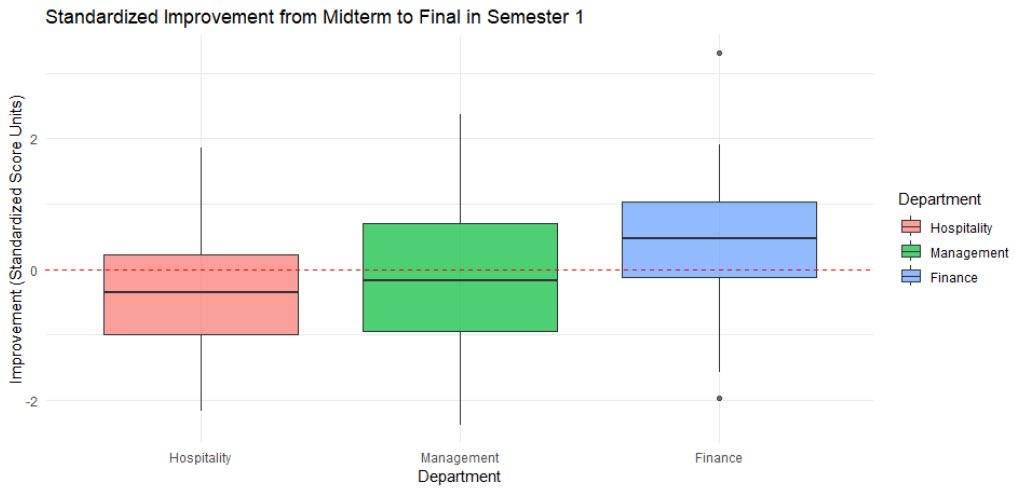
Three-Way Interaction: Sex × Grit × AI Tool Use: Given our finding that Grit moderates the effect of AI tool use on improvement, we tested a comprehensive three-way interaction model to determine if this moderation effect itself differed by sex. The model testing the AI tool use × Grit × sex interaction was statistically significant, $F(9, 91) = 2.13$, $p = .034$, and accounted for 17.4% of the variance in improvement (Adjusted $R^2 = .093$). However, the three-way interaction term was not statistically significant ($\beta = -0.093$, $p = .590$), indicating that the moderating effect of Grit on the relationship between AI tool use and academic improvement does not differ between male and female students.

Hypothesis 3: There is a relationship between academic merit and the use of AI teaching tools and academic performance

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. The final analytic sample consisted of 104 students across three university departments (Hospitality [HTM], n=38; General Management [GTM], n=35; Finance, n=31), with 30 cases excluded due to missing data.

Initial analysis revealed no statistically significant mean improvement from midterm to final examinations at the cohort level in either Semester 1 (Mean $\Delta z = 1.45\text{e-}16$, $p = 1.00$) or Semester 2 (Mean $\Delta z = 2.50\text{e-}16$, $p = 1.00$). However, notable variation in improvement patterns emerged when examining results by academic department (see Figure 1).

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.

A one-way ANOVA confirmed that the department a student belonged to be a significant predictor of improvement in Semester 1, $F(2, 100) = 2.54$, $p = .013$. Post-hoc comparisons using the fitted linear model indicated that, controlling for other factors, students in the Finance department showed greater improvement than those in the Hospitality and Management departments (see Figure 1).

To test the primary hypothesis that using the AI assessment tool predicts academic improvement, two hierarchical linear regression models were constructed, one for each semester. The outcome variable was the standardized improvement score (change z). Predictors included the continuous AI engagement score (AIscore), University department (department), and course repetition status (repeat2).

For Financial Accounting (semester 1), the overall model was marginally non-significant, $F(3, 100) = 2.58$, $p = .058$, and explained approximately 7.2% of the variance in improvement ($R^2 = .072$). Contrary to expectations, the AI engagement score was not a significant predictor of improvement ($\beta = 0.005$, $p = .812$). The only significant predictor was department ($\beta = 0.343$, $p = .013$). For Semester 2, the regression model was non-significant, $F(3, 100) = 0.25$, $p = .859$, and accounted for less than 1% of the variance ($R^2 = .008$). Again, AI engagement was not a significant predictor of improvement ($\beta = -0.001$, $p = .954$).

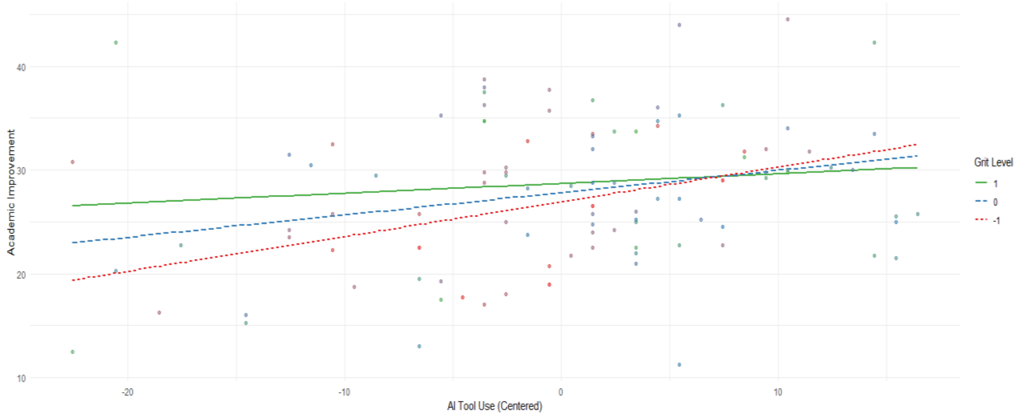
Hypothesis 4: Moderating Role of Personality Traits

Given the non-significant direct effect of AI tool use, we tested whether its effectiveness was moderated by student personality, specifically Grit. A moderation analysis was conducted for Semester 1 data, with standardized improvement as the outcome and the interaction term between Aiscore1 and grit as the predictor, while controlling for department and repetition status.

The moderation model was statistically significant, $F(5, 95) = 3.54$, $p = .006$, and accounted for 15.7% of the variance in improvement (Adjusted $R^2 = .113$). The analysis revealed a significant main effect of Grit ($\beta = 2.09$, $p = .002$) and a significant main effect of AI tool use ($\beta = 0.44$, $p = .002$). Crucially, these main effects were qualified by a significant negative interaction between AI tool use and Grit ($\beta = -0.127$, $p = .002$).

To interpret this interaction, simple slopes were plotted for students with low (1 SD below the mean) and high (1 SD above the mean) levels of Grit (see Figure 2). The analysis indicated that the AI tool was beneficial for students with low Grit ($\beta = 0.44$, $p = .002$), whereas for students with high Grit, the effect of the AI tool was not significant ($\beta = -0.02$, $p = .908$). In essence, the AI assessment tool was particularly effective in promoting academic improvement for students who were lower in the personality trait of Grit.

Figure 2. The Moderating Effect of Grit on the Relationship Between AI Tool Use and Academic Improvement in Semester 1. The positive effect of AI tool engagement on improvement is significant only for students low in Grit



Discussion

The existing literature (Jonhson et al. 2009; Cano and Troya, 2023) suggests that the use of AI tools can enhance students' engagement and academic performance. This finding, however, was observed primarily in the first semester for the Finance Accounting Course but was not replicated in the second semester for Management Accounting. This discrepancy might indicate that the novelty effect of the AI tool diminished, or students perceived that the effort required for engagement did not proportionally translate to improved grades. Interestingly, no significant difference was noted among repeat students. However, in agreement with Zhang and Zoo (2022), we found that engagement with AI-assisted learning tools is associated with improved academic performance, with more pronounced effects in Financial Accounting than Management Accounting.

Further, in agreement with Fachrurrozie et al. (2025), we found that there was no moderating effect between the gender variable, the use of AI teaching tools and academic performance. A particularly interesting finding, contrasting with Wecks et al. (2024), reveals that students with higher academic standing (e.g., Finance students) experienced a significant improvement in academic performance in Semester 1, but not in Semester 2, across both accounting subjects when utilizing the AI teaching tool, as opposed to students with lower academic standing (e.g., Hospitality students).

Finally, a significant contribution of this study is the observation that students with lower grit—specifically a reduced level of perseverance of effort—demonstrated significantly better academic performance when using the AI teaching tool compared to their counterparts with higher grit. Thus, for students with low grit, the AI tool was highly beneficial acting as an 'intelligent scaffolding' that enforced timeframes and discouraged procrastination. For high-grit students, the tool's effect was non-significant, as they likely possess the internal discipline to succeed independently. The finding can be referred to as the "grit paradox" in this study since it describes a significant and counterintuitive interaction between a student's level of personality grit and their engagement with the AI teaching tools. While grit is traditionally a positive predictor of academic success, the sources reveal that AI tools provided the greatest academic benefit to students with low grit.

Conclusions, Policy Implications and study Limitations

A primary limitation of this study is the rather small sample size, comprising of 104 participants, which necessitates replication with a larger cohort to validate the findings. Despite this, the conclusions drawn are reliable and do not relate to perceptions but actual findings because the students included in the analysis were: (a) registered in both Financial and Management Accounting, (b) completed the Personal Grit, and (c) agreed for their personal information (i.e. final marks) to be used for the study.

The authors are aware that students may be answering the personality and grit questionnaires randomly; thus, to address this, the researchers calculated Cronbach's α for all scales, and respondents whose answers significantly lowered the reliability were excluded. In addition, they looked for patterned responses across the data; all unreliable responses were excluded. Another potential limitation, where students might have outsourced the grit scale, was mitigated by administering the scale in class, requiring completion and submission before students left the room. Some students opted not to provide their identity numbers, which precluded the use of their final marks and prevented comparison of grit with AI usage and academic performance, consequently reducing the sample size.

Finally, the limited temporal and geographic scope of the research may affect the generalizability of the results. Thus, this study is suggested to be exploratory and worth replicating with a bigger sample.

Thus, the use of AI teaching tools create a bimodal benefit of intelligent scaffolding by: (a) the accelerator on one side targeting students with high academic merit and uncapping the ceiling for those top performers and (b) creating a safety net for low-grit/ unengaged students through adaptive loops which prevent failure fatigue thus raising the floor for vulnerable students. Hence, AI does not operate uniformly, its impact cascades through a network of individual differences, serving entirely different pedagogical functions based on psychometric profiles.

In conclusion, the superpower of AI in accounting education is not making exams easier, nor is it merely automating the grading process. It is providing an intelligent, tireless scaffold that uniquely rescues the students who are most likely to give up.

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