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Behavioral Intention to Use Artificial Intelligence (AI) Among Accounting Students: Evaluating the Effect of Job Relevance

Kamisah Ismail[a]*, *Jyashree Krishnanraw*[a]
[a]Universiti Malaya, Malaysia

Abstract: This research meticulously evaluates the influence of job relevance on accounting undergraduates' behavioral intentions toward utilizing artificial intelligence (AI), scrutinizing the mediating role of perceived usefulness. Anchored in the extended technology acceptance model (TAM), this study employs a cross-sectional, survey-based methodology to gather data from 136 undergraduate students across various public and private Malaysian universities. The empirical evidence elucidates that job relevance positively influences the students' behavioral intentions regarding AI integration. In tandem, perceived usefulness emerges as a significant mediator, revealing its critical role in this relationship, thus manifesting a partial mediation effect. The findings highlight the necessity of strategically reconfiguring accounting education curricula to incorporate pedagogical approaches aligned with the influential factors of job relevance and perceived usefulness, thereby intensifying students' intentions to engage with AI in academic and professional settings. Such an educational evolution is paramount, equipping accounting students with the requisite competencies and insights to navigate the accounting profession's rapidly transforming, technologically driven landscape.

Keywords: artificial intelligence (AI), accounting education, technology acceptance model, behavioral intention, job relevance, malaysian higher education institutions.
JEL Classification: M410

*Corresponding author's e-mail: kamisah.ismail@um.edu.my

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Introduction

The integration of artificial intelligence (AI) is driving a fundamental transformation in the accounting profession, reshaping traditional financial processes and necessitating a shift toward data-driven decision-making. In Asia, the adoption of AI has accelerated significantly, with countries such as Indonesia, Thailand, Singapore (AACSB, 2014), and Malaysia leading investments in AI-driven financial solutions (Malaysian Investment Development Authority, 2022). Malaysia, in particular, has demonstrated notable progress, advancing from a relatively low AI investment level in 2018 to becoming the second-largest AI investor in the region by 2022. Projections from the International Data Corporation (IDC) indicate that AI investments in the Asia-Pacific region will reach USD 32 billion by 2025, underscoring a rapidly expanding ecosystem of AI applications within financial and business operations (Digital News Asia, 2018).

As AI continues to transform the accounting sector, its adoption has been widely recognized for enhancing operational efficiency, automating routine financial tasks, and improving fraud detection and audit accuracy (Salem, 2012). Across organizations of varying sizes, from multinational corporations to small and medium-sized enterprises, AI-driven tools are increasingly leveraged to optimize financial processes and support strategic decision-making (Lee & Tajudeen, 2020). Consequently, there is a growing expectation for accountants to develop digital proficiency alongside their financial expertise to remain competitive in the evolving professional landscape (Bakarich & O'Brien, 2020; Faizal et al., 2022; Gambhir & Bhattacharjee, 2021; Yigitbasioglu et al., 2023).

Despite the evident integration of AI within professional accounting environments, there remains a significant gap in research regarding how accounting students perceive and engage with AI technologies (Gambhir & Bhattacharjee, 2021; Holmes & Douglass, 2022; Mohammad et al., 2020). Prior studies have predominantly examined students' technological readiness for AI adoption (Damerji & Salimi, 2021), yet limited attention has been given to their behavioral intention to use AI—a key determinant of actual technology adoption and usage (Kwak et al., 2022). Behavioral intention serves as a critical predictor within technology acceptance frameworks, as it directly influences whether individuals transition from awareness of a technology to its active implementation in professional practice (Davis, 1989). Understanding behavioral intention is thus essential in ensuring that students not only acquire theoretical knowledge of AI but are also inclined to integrate AI tools into their future accounting roles.

Furthermore, the absence of structured AI training in many accounting curricula has contributed to a growing skills gap among graduates, as universities struggle to align their educational programs with industry demands (Elo et al., 2023; Gunarathne et al., 2021; Qasim & Kharbat, 2020). While the Malaysian Qualifications Agency (MQA) has emphasized the importance of embedding technological competencies into accounting programs (Malaysian Qualifications Agency, 2014), universities continue to face challenges in developing AI-focused curricula due to the lack of explicit directives and standardized frameworks for AI integration in accounting education (Damerji & Salimi, 2021). This misalignment between academic instruction and professional expectations underscores the urgent need for research that explores the factors influencing students' engagement with AI technologies.

To address this research gap, this study adopts an extended technology acceptance model (TAM) to examine the behavioral intention of accounting students to use AI. The study introduces job relevance (JR) as a key factor shaping students' perceptions of AI's applicability in their prospective careers and perceived usefulness (PU) as a mediating variable, assessing whether students perceive AI as beneficial in enhancing their job performance (Venkatesh & Davis, 2000). By investigating these factors, this research provides valuable insights into how accounting education can better align with AI advancements, ensuring that graduates are equipped with the necessary competencies to navigate an AI-driven professional landscape.

Ultimately, this study makes a significant contribution to the existing body of knowledge on AI adoption in accounting education by offering a comprehensive understanding of the behavioral factors that influence AI usage among accounting students. The findings will provide actionable recommendations for curriculum reform, industry collaboration, and AI policy development, ensuring that future accountants are adequately prepared to integrate AI technologies into their professional practice. Moreover, this research highlights the pressing need for structured AI education in accounting programs, advocating for greater AI investment from academic institutions, government bodies, and corporations to foster economic growth, enhance global competitiveness, and strengthen the role of AI in shaping the future of accounting and financial services.

Literature Review and Hypotheses Development

AI-Powered Evolution in Accounting Practices

AI is commonly defined as systems that possess the ability to learn and reason in a manner similar to human intelligence. Haenlein and Kaplan (2019) define AI as the capability of systems to precisely interpret external data, acquire knowledge from them, and use this information in a versatile manner to achieve particular objectives. AI exhibits a range of intelligence types, including cognitive-analytical, emotional-human-inspired, and social-humanized, mirroring diverse human cognitive abilities. Its inception can be traced back to Asimov's three laws of robotics in 1942 and the Bombe developed by Turing, culminating in the formal establishment of the term 'artificial intelligence' by Minsky and McCarthy in 1956 during a seminal workshop.

Machine learning (ML), an integral facet of AI, profoundly impacts diverse fields, especially accounting, revolutionizing industry norms through its capability for efficient data processing without explicit programming (Kommunuri, 2022). ML significantly refines loss estimation and audit procedures, leading to more precise forecasts (KPMG, 2016), and augments fraud detection and tax classification methods (Ernst & Young, 2017). AI-based robotic process automation (RPA) is revolutionizing accounting by automating tasks such as invoice processing and data validation, significantly reducing routine workloads (Razak & Ismail, 2022). Despite its decision-making constraints (Stafie

& Grosu, 2022), RPA redirects accountants towards more analytical roles, especially in taxation, for enhanced analysis and strategic planning (Deloitte, 2023). This development is notably implemented in firms like Pricewaterhouse Coopers (PwC) and Deloitte, where RPA efficiently handles data collection and tax process automation (Deloitte, 2023; Pricewaterhouse Coopers, 2017). Artificial neural networks (ANN), emulating human neural networks for complex data processing, surpass traditional computing in advanced intelligence (Zhang et al., 2020). In accounting, ANN facilitates intricate tasks like risk assessments, market forecasting, and financial analysis, addressing the sector's demand for high-level analytical capabilities (Kommunuri, 2022). The nascent integration of AI in accounting, particularly by the Big Four, illustrates its growing importance in the industry, reflecting a trend toward diverse applications shaping the sector's future (Zhang et al., 2020).

Behavioral Intention to Use Artificial Intelligence

Behavioral intention (BI) is a fundamental concept in technology utilization and is crucial in predicting individual engagement with AI technologies in accounting. Rooted in social psychology, BI is acknowledged as a primary predictor of actual behavior, especially in contexts of technology use (Fishbein & Ajzen, 1975). Its theoretical foundation extends from the theory of reasoned action (TRA) and the theory of planned behavior (TPB), which posit that BI is influenced by an individual's attitude, subjective norms, and perceived behavioral control, encompassing the interplay of personal beliefs, societal influences, and perceived behavioral ease or difficulty (Ajzen, 1985; Fishbein & Ajzen, 1975; Mohamed Asmy Mohd Thas et al., 2016). Within technology-focused disciplines such as accounting education, the TAM provides an insightful framework for understanding technology use, positing that BI hinges on technology's perceived usefulness (PU) and perceived ease of use (PEOU) (Nicholas et al., 2021). However, critiques, notably by Moon and Kim (2001), highlight TAM's limited scope in capturing the full range of factors influencing technology adoption. While TAM traditionally emphasizes PU and PEOU, recent studies suggest that AI adoption in accounting is increasingly shaped by broader structural elements such as Industry 4.0 readiness, regulatory support, and firms' strategic alignment with AI technologies (Abdullah & Almaqtari, 2024; Muh. Darmin Ahmad et al., 2013). This indicates that, beyond individual perceptions, external technological infrastructures and institutional readiness play a crucial role in BI toward AI adoption in accounting.

To address these limitations, extensions to TAM have incorporated additional context-specific factors. For example, Licen Indahwati (2005) highlights the role of system characteristics such as terminology relevance and screen design in shaping technology acceptance. Building on this expanded perspective, this study focuses on job relevance (JR), which reflects AI's alignment with academic and professional needs, to further validate the applicability of TAM in educational contexts. These enhancements provide a more comprehensive understanding of user expectations. TAM suggests that when AI is perceived as both advantageous and user-friendly, its likelihood of adoption increases (Davis, 1989). The concept of 'attitude,' as defined by the TRA, is essential in technology integration, reflecting individuals' beliefs and expectations toward specific technologies. This is especially relevant for accounting students considering AI in their curriculum. Their attitudes vary from enthusiasm to skepticism, shaped by past experiences, views on AI's academic benefits, and its potential usefulness in their future careers (Compeau & Higgins, 1995; Davis, 1989; Venkatesh et al., 2003; Venkatesh & Bala, 2008; Venkatesh et al., 2016).

Moreover, AI's growing role in accounting education has shifted curriculum priorities as institutions increasingly recognize the necessity of equipping students with specialized data management and analytics skills. Holmes and Douglass (2022) highlight that public accountants, especially within the Big Four firms, exhibit stronger agreement on the need for AI-related skill development than accounting educators, underscoring the profession's proactive stance compared to academia's gradual adaptation. This reinforces the notion that BI toward AI adoption is not solely driven by PU and PEOU but is also shaped by institutional readiness and the evolving demands of professional practice.

Key factors such as PU and JR significantly influence attitudes towards AI. JR assesses the alignment of AI with students' career aspirations, and a strong correlation amplifies its perceived importance (Lai, 2017; Venkatesh et al., 2003). PU, originating from the TAM, measures the belief in AI's capacity to enhance performance, with a positive perception engendering a favorable attitude toward its adoption (Davis, 1989). These elements collectively impact BI and highlight the interplay of perceptions, evaluations, and intentions (Legris et al., 2003; Venkatesh & Davis, 2000).

Contrastingly, in this milieu, the emphasis on subjective norms from the TRA and TPB is diminished. The decision-making process regarding AI integration among accounting students prioritizes individual assessments of technology's relevance to their academic and professional pursuits. Venkatesh and Davis (2000) support this, noting a shift from external influences to intrinsic evaluations. This aligns with findings from Gefen et al. (2003), Wu and Wang (2005), and Jackson et al. (1997), which emphasize individual perceptions over societal norms in technology use intentions. Consequently, for Malaysian accounting students, the focus is on personal evaluations and the utility of AI in their field.

In conclusion, this exploration into BI reveals a pivotal transition towards personal evaluations and the direct relevance of AI in accounting education, signifying a refined comprehension of technology integration in this professional domain.

Job Relevance

In the dynamic progression of AI within the accounting sector, the principle of job relevance (JR) emerges as a critical factor influencing behavioral intention (BI) toward technology integration among professionals. Defined by Venkatesh and Davis (2000), JR examines the perceived congruence of technological innovations with the specific exigencies of a professional role, asserting a vital influence on incorporating advanced technologies in the accounting domain. Insights from Holmes & Douglass (2022), Kieras and Polson (1985), and Polson (1987) underscore individuals' ability to evaluate the applicability of technology within their professional tasks. Moreover, Chong and Chan (2012) amplify this perspective, highlighting JR's role in forming perceptions about technology's inherent value and potential benefits. Sohn (2017) further elaborates on the intrinsic nature of these perceptions, rooted in an individual's understanding of the congruence between technological tools and the specificities of their professional duties. The interplay of JR with PU thus becomes a focal point in determining technology utilization, with the suitability of a technology's features to professional tasks significantly impacting its PU and subsequent usage intentions. This study seeks to meticulously analyze the intricate relationship between JR and the inclination of future accountants to incorporate AI into their professional practices, spotlighting JR's pivotal role in guiding their technological engagement.

Various theoretical frameworks explore the intersection of technology with professional tasks, each contributing to our understanding of this dynamic. As posited by Vessey (1991), the cognitive fit theory underscores that when technology is aligned with an individual's tasks, it improves performance and bolsters problem-solving capabilities. Echoing this sentiment, Leonard-Barton and Deschamps (1988) introduce the concept of 'job-determined importance,' emphasizing how individuals' ascribed value to their roles significantly shapes their engagement with technology, particularly when it directly relates to their job responsibilities. Building upon these ideas, Hartwick and Barki (1994) propose the notion of 'involvement,' suggesting that a deeper, more personal connection with a system enhances its utilization. This notion is further developed by Goodhue (1995) through the 'task-technology fit' construct, advocating for the essential harmony between a technology's capabilities and the demands of a specific task for successful integration. Venkatesh and Davis (2000) expand on this subject by emphasizing the importance of aligning a technology's features with an individual's professional expectations to influence their intention to integrate it positively. This synthesis of theoretical insights underscores the integral role of JR in determining the trajectory of technology integration. JR stands out as a substantial extrinsic influencer that shapes perceptions of a technology's efficacy, particularly in scenarios where professional tasks and technological capabilities are closely intertwined.

Consequently, this research addresses the perceptions of accounting students on the verge of their professional journeys, scrutinizing how their views on AI's congruence with expected job competencies and tasks shape their valuation of AI's utility. This line of inquiry resonates with the findings of Alharbi and Drew (2014) and Rui-Hsin and Lin (2018), which posit that perceptions of technology's utility in future professional scenarios are influenced by its anticipated function. Corroborating this perspective, Thompson et al. (1991) underscore the significance of the alignment between technology and profession-specific tasks in augmenting the technology's perceived utility. Similarly, Kim et al. (2009) articulate the imperative of harmonizing job functions with the capabilities of information systems, asserting that the effectiveness of these systems is fundamentally connected to their relevance to the tasks they support. Thus, these students place significant value on AI tools proficient in advanced data analysis, predictive analytics, and the provision of strategic financial insights, recognizing them as crucial assets for their forthcoming professional pursuits. This perception is rooted in the belief that AI will simplify conventional accounting tasks and enable practitioners to delve into the more advanced, strategic facets of the accounting field.

H1: Job relevance has a direct and positive effect on the perceived usefulness of artificial intelligence.

Adding to the existing discourse, this investigation delves into the relationship between JR and BI in technology use, emphasizing AI in accounting education. It proposes that the perception of AI's pertinence to future professional roles profoundly influences students' readiness to engage with this technology. Supporting this notion, Izuagbe et al. (2022) note a surge in e-database usage among faculty members, linking this increase to the technology's alignment with their professional responsibilities. Complementing this, Smit et al. (2020) demonstrate a strong correlation between student engagement with technology and the alignment of such tools with their career aspirations, thus highlighting the significance of perceived job relevance. Furthering this exploration, Kar et al. (2021) investigate how aligning specific technological skills, particularly in areas such as the Industrial Internet of Things (IIoT), with students' career objectives fosters the acquisition of pertinent expertise. These insights align with the principles of the unified theory of acceptance and use of technology (UTAUT), as articulated by Venkatesh et al. (2003) and the extension of the TAM by Venkatesh and Davis (2000), which assert a direct correlation between the perceived professional relevance of technology and its adoption and effective utilization. This alignment suggests that when students perceive technologies like AI as vital to their professional success, they are more inclined to learn and apply them, thus enhancing their skills and marketability. Consequently, in accounting education, where AI is gaining prominence as an essential tool, the perception of AI's JR is likely to affect students' BI to engage with AI significantly. Those who view AI as indispensable to their future roles are more likely to embrace and utilize these technologies.

H2: Job relevance directly and positively affects the behavioral intention to use artificial intelligence.

Perceived Usefulness

Perceived usefulness (PU), a fundamental construct in understanding the utilization of technology, particularly AI in accounting education, originates from the TAM introduced by Davis (1989). Building on the theory of reasoned action (TRA) by Fishbein and Ajzen (1975), the TAM identifies PU as a key factor influencing users' intention to utilize technology. This model emphasizes the importance of perceived benefits in enhancing job performance (Davis, 1989). Subsequent extensions, such as the TAM2 and the UTAUT by Venkatesh et al. (2003), incorporate additional factors like social influences and facilitating conditions, while maintaining PU as a fundamental determinant in technology acceptance.

The focus on PU, distinct from PEOU, is substantiated by research highlighting its independent predictive capability. Studies by Mathieson (1991) and Keil et al. (1995) demonstrate that PU's influence on user intentions can be decisive even when ease of use is not a significant concern. These findings underscore the integral role of PU in shaping user attitudes and BI toward technology, making it a crucial factor for curriculum development and educational strategy, especially in fields rapidly evolving with technology, such as accounting. The direct positive effect of PU on BI to use AI in accounting education is well-supported by empirical evidence, underscoring how students' perceptions of AI's utility influence their engagement. Research across various domains consistently demonstrates PU's significant impact on BI. Studies by Venkatesh and Bala (2008) and Chang and Tung (2007) highlight PU as a robust predictor of technology use intentions. These findings are validated across a spectrum of fields, mobile commerce (Tao, 2011), e-learning (Sánchez & Hueros, 2010), and healthcare (Yi et al., 2006), thereby affirming the extensive applicability of this correlation. Karahanna and Straub (1999) emphasize that early adopters of information technology regard PU as a vital element in influencing their attitudes and behaviors towards emerging technologies. This insight is critical when considering accounting students, who are often at the forefront of encountering and integrating new technological tools in their education. The belief that AI can significantly enhance their job performance and efficiency is likely to foster a positive attitude towards using AI in their studies and future professional practice. For instance, if students perceive AI as a tool that can aid in complex data analysis, enhance decision-making, or offer predictive insights—skills highly relevant to the accounting profession—this perception of usefulness is expected to increase their intention to use AI.

H3: Perceived usefulness has a direct positive effect on behavioral intentions to use artificial intelligence.

Perceived Usefulness as a Mediator

Within the intricate framework of accounting education, the interrelation between job relevance (JR), perceived usefulness (PU), and behavioral intention (BI) in utilizing AI is elucidated through a multifaceted process. Initially, accounting students evaluate JR to determine AI's alignment with their prospective professional responsibilities (Venkatesh & Davis, 2000). This evaluation establishes a foundational belief, catalyzing the cognitive trajectory toward technology usage. Following this assessment, the focus shifts to appraising PU, with Mathieson (1991) emphasizing AI's perceived utility in occupational tasks and highlighting its significant influence on students' propensity to use the technology. PU thus transcends its role as a mere additive element, serving instead as an augmentative agent that amplifies the influence of JR on BI. This intermediary effect of PU is further delineated by Son et al. (2012), suggesting that PU intensifies the impact of JR on BI. Students' acknowledgment of AI's efficacy in enhancing job performance consolidates their intention to employ AI, extending beyond mere recognition of JR. Empirical findings by Venkatesh and Bala (2008) substantiate this interplay, illustrating that within the dynamic sphere of accounting technology, students' discernment of AI's utility, informed by its JR, is instrumental in shaping their behavioral inclinations.

H4: Job relevance indirectly influences behavioral intention to use artificial intelligence through the mediator, perceived usefulness.

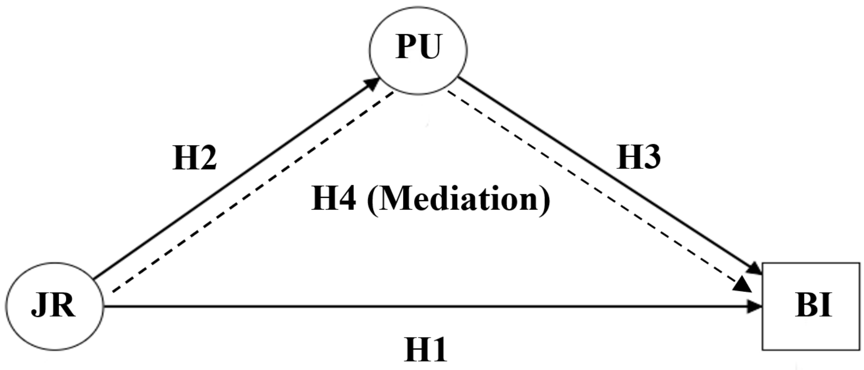

Figure 1. Research Framework

Notes: *JR= Job Relevance, PU= Perceived Usefulness, BI= Behavioral Intention*

Methods

Population and Samples

This study employs a cross-sectional quantitative analysis underpinned by a positivist philosophy, which advocates for objectivity and systematic measurement (Davis & Fisher, 2018). In contrast to qualitative research, which explores descriptive and interpretative aspects, this methodology emphasizes quantification (Coolican, 2009). A deductive approach is utilized to systematically test pre-formulated hypotheses against empirical data, aligning with the study's quantitative and theoretical orientation (Kumar, 2014).

This study meticulously examines the attitudes of third- and fourth-year undergraduate accounting students from four eminent Malaysian universities: Universiti Malaya (UM), Universiti Kebangsaan Malaysia (UKM), Sunway University (SU), and Multimedia University (MMU). The rationale for focusing on students at this advanced stage of their academic journey is their profound comprehension of the curriculum and an enhanced awareness of the accounting industry's requirements. This advanced understanding is essential for generating precise and reliable responses, a quality that may be compromised when obtaining feedback from students in the early stages of their undergraduate program.

These institutions were selected for their exemplary reputation in accounting education and geographic convenience for research, offering diverse perspectives to the study. UM and UKM are renowned for their comprehensive accounting programs and pioneering efforts in integrating AI into research, reflecting their commitment to technological advancement in accounting. Conversely, SU and MMU are acknowledged for their focus on technology and global academic partnerships. This blend of public and private universities allows the study to provide an extensive and nuanced analysis of student perceptions concerning the integration of AI in accounting education, specifically regarding their BI toward utilizing AI. The sample was gathered through convenience sampling, a strategy endorsed by Saunders et al. (2019) for its practicality and accessibility. Out of the 1,244 students across the selected universities, the study aimed for a representative sample of 294 based on statistical requirements for a 95% confidence level and a 5% margin of error (Bryman & Bell, 2015). The final participant count was 136 students, reflecting a 46.26% response rate.

The observed response rate in the study is moderate, but caution is warranted due to potential response biases that may affect the findings. According to Bogner and Landrock (2016), satisfying behavior may lead respondents to provide less cognitively demanding answers rather than truthful opinions. Additionally, social desirability bias could pressure students to overstate their readiness for AI to meet perceived academic or industry expectations. These factors may result in overestimations of behavioral intentions toward AI adoption and inconsistencies in self-reported attitudes, highlighting the need for careful interpretation of the results.

Despite these potential biases, the study exhibits a level of statistical robustness that merits consideration. Bhattacherjee (2012) notes the inherent challenges in achieving high participation rates in specialized quantitative research, while Vasileiou et al. (2018) emphasize the importance of data integrity over mere response volume. Moreover, the sample size adheres to the criteria established by Hair et al. (2021), specifically the ten-times rule, thereby confirming the dataset's adequacy for rigorous hypothesis testing. Nonetheless, it remains essential for future research to investigate alternative sampling techniques or to conduct follow-ups with non-respondents, as these strategies may further mitigate bias and enhance the generalizability of the results.

Data Collection

Prior to distributing the questionnaire, ethics clearance was obtained from the Universiti Malaya Research Ethics Committee (UMREC), which reviews all non-medical research involving human participants, including methodology, risks, recruitment, consent, confidentiality, and data management. Participant recruitment was strategically focused on individuals who were both accessible and willing, employing an online survey using Google Forms as the primary data collection method. This survey was disseminated to qualified undergraduate accounting students in their penultimate and final years at selected universities using their official university email addresses. The emails provided a comprehensive overview of the study, including its objectives, survey duration, participation criteria, confidentiality assurances, and the voluntary nature of participation. Furthermore, students were apprised of the study’s purpose and the subject of AI to ensure well-informed and pertinent responses. The study diligently adhered to the involved institutions' stringent ethical guidelines and procedures while upholding the participants' rights and welfare. Participants were assured that their responses would remain confidential to ensure anonymity and encourage candid feedback, with only aggregated results being reported. Prior to the survey, participants were mandated to give electronic approval, facilitated through a consent statement at the beginning of the survey. Confronted with an initial low response rate, the researcher implemented several strategies to enhance participation, including sending reminder emails and obtaining faculty endorsements to encourage survey completion. Lecturers in core courses were solicited to promote the survey, and it was also disseminated through accounting clubs and societies at the universities, aiming to expand its reach without disrupting classes.

Measurement of Variables

The study was conducted with meticulous attention to ensuring the validity and reliability of the quantitative survey instrument. The questionnaire was systematically developed, drawing from scholarly literature, and organized into two primary sections: demographics and specific constructs. The demographic section captured data about academic year, ethnicity, university affiliation, nationality status, and gender. To evaluate JR, two indicators were sourced from Venkatesh and Davis (2000). The PU construct comprised six items adapted from Davis (1989). The final segment, centered on BI regarding AI utilization, encompassed three components derived from the framework outlined by Davis (1989). A 7-point Likert scale, spanning from strong disagreement (1) to strong agreement (7), was utilized to elicit responses. This scale allowed respondents to articulate their level of agreement with each statement accurately. Table 1 below provides a detailed summary of the measurement sources for these variables, ensuring a clear and comprehensive understanding of the constructs assessed within the study.

Table 1. Measurement of Variables

Variables	Main Sources
Job Relevance (JR)	Venkatesh and Davis (2000)
Perceived Usefulness (PU)	Davis (1989)
Behavioral Intention (BI) to Use	Davis (1989)

Data Cleaning

The data cleaning process for the survey, initially consisting of 138 responses, was executed with rigorous attention to ensure data integrity. This process involved removing duplicate entries, scrutinizing straight-lining patterns for respondent bias, and thoroughly evaluating outliers, resulting in a final dataset of 136 responses. These measures ensured the creation of a robust and credible dataset suitable for comprehensive analysis (Duraj & Szczepaniak, 2021; Kwak & Kim, 2017).

Results

Descriptive Statistics

This study employs IBM SPSS to analyze the demographic characteristics of the participants, as summarized in Table 5.1, providing a comprehensive overview of the sample composition. The majority of respondents are third-year students (61.8%), while fourth-year students (38.2%) are comparatively fewer. This distribution is attributed to academic structures and commitments, particularly in universities where final-year students engage in intensive coursework, industry placements, and internships, limiting their availability for research participation. At Sunway University (SU), where the accounting program spans three years, third-year students represent the graduating cohort, further explaining their higher representation. The inclusion of students at this stage is particularly relevant as they are on the verge of transitioning into the workforce, making their perceptions of AI adoption in accounting more pertinent.

The sample is well-balanced across public (53.7%) and private (46.3%) universities, ensuring representation from institutions with varying levels of AI integration and curriculum emphasis. Among the participating institutions, the Universiti Malaya (UM) has the highest representation (29.4%), followed by Multimedia University (MMU) at 27.9%, Universiti Kebangsaan Malaysia (UKM) at 24.3%, and Sunway University (SU) at 18.4%. Public universities may provide broader exposure to AI through government-funded digital transformation initiatives, while private universities often integrate AI through industry collaborations and specialized training programs.

Ethnic composition within the sample reflects a majority of Chinese students (58.1%), followed by Malay (25%) and Indian (16.9%) students. This distribution is consistent with demographic trends in Malaysian public and private universities, where certain ethnic groups exhibit stronger representation in technology-related and accounting disciplines (Sua & Santhiram, 2017; Suhaili et al., 2019). Additionally, Leung et al. (2011) highlight the influence of cultural and parental expectations in shaping students' career preferences, particularly within the Chinese community, where accounting is perceived as a prestigious and stable profession.

The dataset is predominantly composed of Malaysian students (98.5%), reflecting the study's primary focus on local accounting education and AI adoption. The minimal participation of international students (1.5%) aligns with ICEF Monitor (2023), which reports an increasing number of international student enrollments in Malaysia but a relatively lower representation in AI-focused accounting programs. A notable gender imbalance is observed, with female students comprising 75.7% of the sample, compared to male students at 24.3%. This disparity is consistent with educational trends in accounting, where female enrollment is generally higher. Wan (2017) suggests that certain academic disciplines exhibit a strong female majority, a trend that is evident within accounting programs. The high representation of female students in this study may also indicate a growing interest in AI applications within business and finance among women.

Table 2. Demographic Profiles of the Respondents

		Frequency	Percentage
Academic Year	Year 3	84	61.8
	Year 4	52	38.2

University	UM	40	29.4
	UKM	33	24.3
	SU	25	18.4
	MMU	38	27.9
Ethnicity	Malay	34	25
	Chinese	79	58.1
	Indian	23	16.9
Nationality	Malaysian	134	98.5
	Others	2	1.5
Gender	Male	103	75.7
	Female	33	24.3

Notes: *N = 136. UM = Universiti Malaya, UKM = Universiti Kebangsaan Malaysia, SU = Sunway University, MMU = Multimedia University. Percentages (%) are based on the total sample.*

Table 3. Mean Comparison of Groups (Public and Private Universities)

Constructs	**Public Universities (UM, UKM)**	**Private Universities (SU, MMU)**
	Mean	
JR	6.12	5.95
PU	5.99	5.99
BI to use AI	6.32	5.98

Notes: *JR = Job Relevance, PU = Perceived Usefulness, BI = Behavioral Intention, AI= Artificial Intelligence. Mean values are measured on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).*

Comparative Analysis

A comparative analysis of public (UM, UKM) and private (SU, MMU) universities, as presented in Table 5.2, provides insights into students' perceptions of AI adoption in accounting. The findings indicate a general alignment in AI attitudes, with minor variations in key constructs such as BI and JR. BI scores are higher among public university students (6.32) compared to private university students (5.98). This suggests that students from public universities exhibit greater confidence or willingness to adopt AI technologies, potentially due to higher institutional exposure to AI-driven initiatives, government-backed research projects, and structured curriculum enhancements. Public universities may provide stronger AI integration in accounting education, equipping students with a clearer understanding of AI's role in professional accounting practices.

Similarly, JR scores are marginally higher among public university students (6.12) compared to private university students (5.95). This indicates that students in public institutions may perceive AI as more closely aligned with their future careers, possibly due to greater emphasis on AI applications in accounting courses, career fairs, and industry engagements. While both groups recognize the importance of AI, students from public institutions may have broader exposure to AI's practical applications.

Interestingly, PU scores are identical (5.99) across both groups, signifying a universal recognition of AI's benefits in accounting education and professional practice. This finding aligns with previous research suggesting that PU is a key determinant of technology adoption (Chau & Hu, 2002; Hwa et al., 2015). Despite differences in BI and JR, students from both public and private institutions acknowledge AI as a valuable tool for automation, data analytics, and decision-making in accounting.

Beyond these primary constructs, additional findings reveal subtle differences in institutional support, self-efficacy, and exposure to AI-related technologies. While students from both university types express positive attitudes towards AI adoption, their engagement levels are influenced by institutional resources, curriculum design, and accessibility to AI-driven learning experiences.

Evaluation of Measurement Model

In PLS-SEM analysis, an initial evaluation of the measurement model is imperative to ascertain its reliability and validity. Subsequently, scrutinizing the structural model is essential to ensure the trustworthiness of the data and the accuracy of the outcomes, which involves verifying the findings' consistency (reliability) and precision (validity) (Altheide & Johnson, 1994; Mohajan, 2017).

Convergent Validity

Convergent validity in this study is determined using Average Variance Extracted (AVE), measuring the correlation of indicators within a construct. Validity is confirmed when AVE exceeds 0.5, indicating substantial variance explanation by the construct, as presented in Table 4 (Bagozzi & Yi, 1988; Hair et al., 2013). Furthermore, as illustrated in Table 4, the outer loading values are scrutinized to gauge the robustness of the indicator-construct relationships, with values surpassing 0.70 signifying substantial associations. Values between 0.4 and 0.7, signifying moderate associations, might necessitate removal to improve reliability and AVE (Hair et al., 2014).

Table 4. Measurement Model

Variable	Items	Loadings	AVE	CR
BI	BI1	0.942	0.872	0.953
	BI2	0.95		
	BI3	0.909		
JR	JR1	0.948	0.905	0.95
	JR2	0.955		
PU	PU1	0.862	0.794	0.958
	PU2	0.908		
	PU3	0.901		
	PU4	0.91		
	PU5	0.894		
	PU6	0.868	0.872	0.953

Internal Consistency Reliability

Internal consistency reliability in this study is evaluated using Cronbach's alpha and composite reliability; metrics ranging from 0 to 1 assess the coherence of items within constructs. Consistent with the standards proposed by Nunnally (1978), a Cronbach's alpha above 0.7, as achieved by all constructs in Table 4, denotes high reliability. Composite reliability, encompassing rho_a and rho_c, offers a more nuanced assessment by considering the distinct contributions of individual indicators. These metrics exceed the 0.7 thresholds in this study, affirming strong internal consistency and substantiating the reliability of the constructs within the PLS-SEM framework.

Discriminant Validity

Discriminant validity, which ensures that each construct is conceptually and statistically distinct, is assessed in this study using the Heterotrait-Monotrait (HTMT) ratio. The HTMT criterion, established by Henseler et al. (2014), evaluates construct distinctiveness by measuring the ratio of between-construct correlations. A threshold of 0.85 is applied, where values below this limit indicate that constructs are sufficiently discriminant (Kline, 2011). As presented in Table 5, all HTMT values fall below the established threshold, confirming discriminant validity and ensuring the measurement model's robustness and reliability.

Table 5. Heterotrait-Monotrait (HTMT) ratio

Items	BI	JR	PU
BI			
JR	0.583		
PU	0.569	0.511	

Collinearity Analysis

Collinearity analysis employs the variance inflation factor (VIF) to identify significant correlations among indicators, potentially leading to challenges in interpreting the model. A VIF value above 5 indicates problematic collinearity that could affect the variance of coefficient estimates, thereby undermining the model's statistical validity (Hair et al., 2021). Indicators such as BI2 and PU2 with the VIF values exceeding this threshold have been removed from the analysis to preserve the model's integrity and reliability, as illustrated in Table 6.

Table 6. Full Collinearity Testing

Items	VIF
BI1	4.741
BI2	5.117
BI3	2.721
JR1	2.911
JR2	2.911
PU1	3.485
PU2	5.102

PU3	4.354
PU4	4.222
PU5	4.189
PU6	3.076

Common Method Bias (CMB) and Predictive Validity Assessment

Table 7. Harman's Single-Factor Test for Common Method Bias

Component	Total Initial Eigenvalue	% of Variance	Cumulative %
1	6.524	59.31%	59.31%
2	1.687	15.34%	74.64%
3	1.003	9.12%	83.76%
4	0.449	4.08%	87.84%
5	0.315	2.87%	90.71%
6	0.265	2.41%	93.11%
7	0.216	1.96%	95.07%
8	0.188	1.71%	96.78%
9	0.152	1.38%	98.16%
10	0.112	1.02%	99.18%
11	0.09	0.82%	100.00%

The Harman's single-factor test revealed that the first factor accounted for 59.3% of the total variance, exceeding the conventional 50% threshold (Podsakoff et al., 2003). While this may indicate potential common method bias (CMB), recent literature suggests that variance levels up to 60% remain acceptable (Fuller et al., 2015). To further validate the findings, full collinearity testing confirmed that the VIF values remained below 5 after the removal of PU2 and PU5, mitigating concerns of multicollinearity-driven bias (Hair et al., 2021). Additionally, the measurement model exhibited strong reliability and validity, with CR exceeding 0.7 and AVE surpassing 0.5 (Fornell & Larcker, 1981). Discriminant validity, assessed using HTMT values below 0.85 (Henseler et al., 2014), confirmed the distinctiveness of constructs, further reducing concerns of CMB.

PLS-predict analysis (Table 8) further validates the findings, demonstrating strong predictive accuracy of the PLS-SEM model, as evidenced by negative PLS-LM values for BI1 (-0.004), BI3 (-0.010), PU3 (-0.006), PU4 (-0.011), PU5 (-0.016), and PU6 (-0.006). While PU1 (0.006) marginally favors the linear model, its Q^2_predict value remains positive (0.129), confirming predictive relevance. Given that all Q^2_predict values are positive, the findings support the robustness and generalizability of the PLS-SEM model, affirming its suitability for predictive analysis (Shmueli et al., 2016). These results indicate that while Harman's test suggests potential CMB, the model's robustness—evidenced by measurement validity, discriminant validity, and predictive accuracy—confirms the reliability and practical significance of the findings.

Table 8. PLS-Predict

Item	PLS RMSE	LM RMSE	PLS-LM	Q²_predict
BI1	0.856	0.86	-0.004	0.165
BI3	0.879	0.889	-0.01	0.188
PU1	0.927	0.921	0.006	0.129
PU3	0.915	0.921	-0.006	0.106
PU4	0.924	0.935	-0.011	0.124
PU5	0.871	0.887	-0.016	0.127
PU6	0.862	0.868	-0.006	0.086

Evaluation of Structural Model

Hypothesis Testing

This research employs bootstrapping in SMART PLS 4 to scrutinize direct and indirect effects, as delineated in Table 9. It delves into hypotheses through path coefficients and p-values, explicitly emphasizing the mediating role of PU.

Table 9. Hypothesis Testing

Hypothesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI LL	BCI UL	f2	VIF	Decision Supported
H1	JR →PU	0.473	0.112	4.219	0	0.196	0.642	0.289	1	Supported
H2	JR →BI	0.371	0.121	3.067	0.002	0.253	0.678	0.174	1.289	Supported
H3	PU →BI	0.354	0.12	2.945	0.003	0.082	0.536	0.158	1.289	Supported
H4	JR → PU → BI	0.167	0.054	3.102	0.002	0.045	0.256	N/A	N/A	Supported

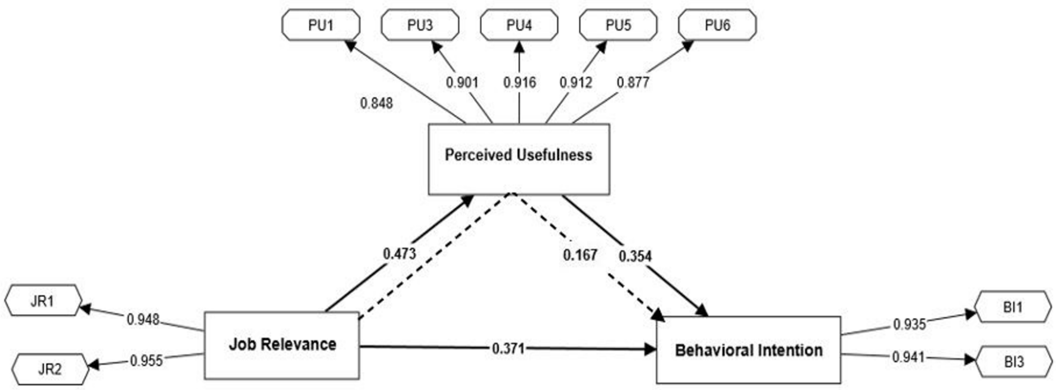

Figure 2. Structural Model of Behavioral Intention (BI)

Information:

: Direct Effect

: Indirect Effect

: Reflective Indicator Measurement

The findings presented in Table 10 demonstrate that all direct effect hypotheses (H1 to H3) exhibit noteworthy p-values and positive path coefficients, thereby substantiating their validity. Additionally, the mediation analysis yields significant results, affirming the favorable mediating influence of PU as postulated in hypothesis 4.

Discussion

The positive and significant influence of job relevance (JR) on perceived usefulness (PU), as evidenced in the validation of Hypothesis 1 ($\beta = 0.473$, $p < 0.05$), reinforces the notion that students' Alharbi and Drew (2014) highlight that educators value learning management systems when they align with core teaching tasks, a finding echoed in (2019), who emphasize the necessity of linking AI tools to specific job objectives. Venkatesh and Davis (2000) further substantiate that JR significantly impacts PU, as users tend to acknowledge the usefulness of technology that closely aligns with their professional functions. In the accounting field, where precision and efficiency are paramount, students' perception of AI's usefulness is heightened when they recognize its practical relevance to critical tasks such as data analytics, automation, and fraud detection. This aligns with prior findings that students and professionals alike value AI technologies that optimize routine processes, enhance decision-making accuracy, and improve audit efficiency (Faizal et al., 2022; Gambhir & Bhattacharjee, 2021). The observed correlation between JR and PU indicates that AI's applicability in real-world accounting scenarios fosters a stronger inclination to perceive it as an essential professional tool rather than a theoretical concept.

The study further validates Hypothesis 2 ($\beta = 0.371$, $p < 0.05$), affirming that JR directly influences behavioral intention (BI) to use AI. This supports Kar et al. (2021), who found that students are more likely to adopt technology when they perceive it as critical to career success. Similarly, Izuagbe et al. (2022) identified a strong connection between JR and faculty members' willingness to use e-databases, further reinforcing the idea that technology adoption is primarily driven by its perceived career relevance. However, this study's findings contrast with research that suggests AI adoption may be influenced more by institutional factors, such as access to AI-based tools, faculty endorsement, or curriculum integration, rather than personal perceptions of JR. Similarly, Lee and Tajudeen (2020) found that regulatory and ethical concerns in AI usage for financial reporting posed significant barriers to adoption, factors not explicitly accounted for in this study. This suggests that while JR plays a crucial role in shaping AI adoption intention, its effects may be moderated by broader institutional and industry-specific constraints.

The research findings elucidate the intricate correlation between PU and BI to employ AI among accounting students. While Hypothesis 3 ($\beta = 0.354$, $p < 0.05$) supports the positive influence of PU on BI, prior research suggests that PU alone may not be a sufficient predictor of actual technology adoption. Chau and Hu (2002) and Hwa et al. (2015) argue that while users acknowledge the usefulness of AI, their BI is contingent on ease of implementation, accessibility, and institutional support. However, this study's findings contrast with research that suggests students' adoption of AI is driven more by social influence and self-efficacy rather than PU alone. Lin and Hsieh (2007) and Buyle et al. (2018) argue that the rapid evolution of AI technology presents a significant barrier to adoption, as students struggle to establish stable, long-term PU, thereby affecting their willingness to engage with AI. Furthermore, Qasim and Kharbat (2020) highlight gaps in accounting curricula that hinder students from fully realizing AI's practical benefits, reinforcing the notion that PU must be complemented by hands-on training and industry engagement.

The findings indicate that PU partially mediates the relationship between JR and BI ($\beta = 0.167$, $p < 0.05$), supporting Hypothesis 4. This suggests that while students perceive AI as useful when it aligns with their future careers, additional factors—such as hands-on experience, self-efficacy, and institutional support—also influence their intention to adopt it. Agarwal and Prasad (1999) propose that PU facilitates the translation of JR into actual technology adoption; however, Damerji and Salimi (2021) found that skepticism regarding AI's reliability in financial reporting weakens this effect among professionals. These findings emphasize that while PU enhances AI adoption, addressing systemic challenges such as curriculum gaps, limited access to AI tools, and regulatory constraints is essential for effective AI integration in accounting education.

Conclusion

This study extends the TAM by identifying JR and PU as key factors influencing accounting students' intentions to adopt AI in their future careers. By analyzing responses from 136 third- and fourth-year undergraduate students across four Malaysian universities, the findings confirm that students are more likely to engage with AI when they perceive it as directly relevant to their professional roles. This underscores the need for accounting education to move beyond theoretical exposure and incorporate practical AI applications, ensuring students develop both technical proficiency and strategic understanding of AI in accounting.

Additionally, the study highlights PU as a critical enabler of AI adoption, reinforcing that students are more inclined to use AI when they recognize its potential to improve efficiency and accuracy in accounting tasks. However, AI adoption is also influenced by factors beyond PU, including institutional support, hands-on training, and industry engagement. Addressing these elements will be crucial in ensuring AI becomes an integral part of accounting education. These findings call for a proactive approach in shaping AI-driven accounting curricula, fostering industry collaboration, and ensuring students gain practical exposure to AI technologies. Future research should explore long-term adoption trends, regulatory considerations, and evolving AI competencies within the accounting profession to further bridge the gap between education and industry demands.

Practical Implications

The findings of this study provide significant insights for accounting educators, policymakers, and accreditation bodies, emphasizing the need to integrate AI competencies into accounting education. To adequately prepare graduates for AI-driven professional environments, universities should incorporate AI-focused modules into accounting curricula, ensuring a balance between theoretical knowledge and practical applications. Regular curriculum updates, aligned with technological advancements and industry expectations, will enhance students' proficiency in AI-related tools. Additionally, structured training programs, workshops, and career counseling initiatives should be introduced to equip students with the necessary skills to navigate an increasingly digital accounting landscape.

Beyond academia, this study highlights key policy implications for accounting firms and certification bodies such as CPA, ACCA, and IFRS. As AI becomes integral to financial reporting, auditing, and decision-making, regulatory bodies should incorporate AI proficiency as a core competency in professional certifications. This ensures that future accountants not only understand AI applications but can effectively implement them in compliance with industry standards. Additionally, accounting firms should integrate AI training into professional development, establish competency benchmarks, and embed AI literacy in recruitment and career advancement criteria. Additionally, regulatory discussions should address the ethical, governance, and compliance challenges associated with AI adoption in accounting. As AI continues to transform financial processes, it is essential to develop industry-wide guidelines to ensure its responsible and transparent use in financial reporting, auditing, and advisory services. Governments and professional bodies should allocate resources and funding to support AI research and education, fostering a workforce that is well-equipped to operate within AI-enhanced accounting environments.

Theoretical Implications

This study enhances the TAM, TRA, and TPB by integrating JR as a key determinant of AI adoption, expanding these models beyond individual perceptions to include career-driven influences. The findings demonstrate that JR significantly impacts PU and BI, strengthening the TAM's predictive capability, aligning the TRA with professional relevance, and reinforcing the TPB through perceived control over AI adoption. These refinements enhance the applicability of the models in educational and professional settings, offering a more comprehensive framework for technology adoption in career-driven environments.

The inclusion of JR as an independent variable provides deeper insights into the factors shaping students' attitudes and BI toward AI, ensuring that the TAM more accurately reflects real-world technology adoption in education. Additionally, this study lays the groundwork for future research on AI adoption in accounting education, encouraging further refinement of the TAM through the identification of additional influencing factors. Addressing previously overlooked variables will support the development of more robust theoretical models, contributing to effective educational strategies and policy development. This advancement underscores the necessity of continuous exploration into AI-related adoption behaviors, ensuring theoretical frameworks remain adaptable to evolving technological and professional landscapes. Furthermore, both direct and indirect relationships are crucial in understanding AI adoption. Direct effects confirm that JR independently influences BI, while indirect effects reveal that PU mediates this relationship, amplifying its impact. Recognizing both provides a comprehensive view of causality, ensuring that AI adoption strategies address not only career relevance but also students' perception of AI's practical benefits.

Limitations

This study constitutes a significant advancement in understanding the integration of AI within accounting education. It identifies critical limitations that necessitate meticulous consideration to accurately interpret its findings. The research focuses on Malaysian undergraduate accounting students in their third and fourth years and encounters challenges in generalizability due to the non-random selection of universities, influenced by factors such as geographical accessibility and institutional reputation. Data aggregated from multiple universities enhances the sample's representativeness. Nonetheless, future research endeavors should strive for broader diversity in educational and cultural contexts to enhance the understanding of student perspectives on AI in accounting education. Furthermore, the adequacy of the current sample size could be improved by expanding it in subsequent studies, which would enhance the statistical power and reliability of the findings. It is imperative to address variations in program structures across universities, including those observed at Sunway University, for a thorough analysis. Future investigations should probe additional factors potentially underexplored to attain more profound insights into student engagement with AI in accounting. In summary, this research provides valuable insights into the intentions of accounting students to utilize AI. However, comprehensive exploration is essential to overcome these limitations and develop effective curriculum integration strategies in the evolving field of accounting.

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