Behavioural Intention to use Artificial Intelligence (AI) among Accounting Students: Evaluating the Effect of Technology Readiness

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ABSTRACT

This research examined the factors influencing Malaysian accounting students' use of Artificial Intelligence (AI) through an extended Technology Acceptance Model. Amid the growing integration of AI in Asia's accounting sector, this study examined the perceptions and intentions of future professionals toward its use. A cross-sectional, survey-based methodology was employed, targeting third and fourth-year undergraduate students from four prominent Malaysian universities, both public and private. The survey evaluated technology readiness aspects, including optimism, innovativeness, discomfort, and insecurity, alongside superior functionality and perceived usefulness. Data from 136 respondents were analysed using Smart PLS 4, assessing the direct and indirect influences on the behavioural intention to use AI. The results revealed that optimism and innovativeness positively impacted perceptions of AI's functionality, with optimism additionally affecting perceived usefulness. However, these factors did not significantly enhance the intention to use AI. Notably, superior functionality acted as a crucial intermediary, linking positive perceptions with usage intentions. In contrast, discomfort adversely affected this intention, highlighting it as a significant barrier to AI engagement. The findings highlight the need for curricular updates in accounting education to mitigate technological discomfort and emphasize critical areas for enhanced AI integration and engagement, aligning with technological progress and the profession's changing demands.

Keywords: Artificial Intelligence, Accounting Education, Technology Acceptance Model, Behavioural Intention, Technology Readiness Dimensions

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INTRODUCTION

The profound transformation within the accounting sector, precipitated by technological advancements, has been notably accelerated by the integration of Artificial Intelligence (AI). This evolution is particularly pronounced in Asia, with nations such as Indonesia, Thailand, Singapore, and Malaysia at the forefront of AI adoption. Notably, Malaysia has experienced a substantial increase in AI investment, escalating to $17.6 billion, with forecasts predicting a rise to $32 billion by 2025 (Malaysian Investment Development Authority, 2022). These investments underscore the pivotal role of AI in sustaining competitive advantage in the global marketplace. The incursion of AI into accounting has catalysed a paradigm shift towards enhanced analytical and advisory roles, necessitating a fusion of traditional accounting expertise with proficiency in digital technologies. This shift underscores the imperative for continuous professional development to navigate the sector's rapid evolution (Gambhir & Bhattacharjee, 2021).

In the prevailing landscape, whilst practitioners often acquire training in advanced technologies through their employment, a discernible gap exists between the competencies fostered by academic institutions and those requisitioned by the professional sector. Graduates frequently emerge with a deficiency in these advanced technological skills, positioning them at a competitive disadvantage within the job market (Ahmad, 2020). This discrepancy accentuates the urgent necessity for academic institutions to recalibrate their curricula to align with the dynamic requisites of the industry, a challenge entailing the incorporation of AI acumen whilst preserving the foundational precepts of accounting (Elo et al., 2023). The Malaysian Qualifications Agency (MQA) has reiterated the importance of integrating technological proficiencies into accounting curricula, an essential measure to prepare students for a technologically driven work environment (Malaysian Qualifications Agency, 2014). However, the absence of comprehensive guidelines for such educational reforms constitutes an ongoing impediment.

In light of AI's escalating significance in the domain, an in-depth understanding of accounting students' perceptions and intentions concerning AI is imperative. Although extensive research has been conducted on AI's impact on the profession (Abdullah & Almaqtari, 2024; Gambhir & Bhattacharjee, 2021; Holmes & Douglass, 2022; Mohammad et al., 2020), the interaction between accounting students and AI technologies has received limited scrutiny. Students' technological readiness and attitudes towards AI adoption have been investigated (Damerji & Salimi, 2021). However, the exploration of their behavioural intentions to utilise AI—a critical determinant of actual usage—remains scant. This inquiry is crucial, as behavioural intentions often serve as precursors to actual technology utilisation. The insights derived from such research are invaluable for universities in developing educational programs congruent with industry standards, thereby ensuring the relevance and contemporaneity of academic training (Kwak et al., 2022). The primary aim of this study was to explore the factors influencing the behavioural intention of accounting students to utilise AI through the lens of an extended Technology Acceptance Model (TAM). The specific objectives are delineated as follows:

1. To examine whether technology readiness (TR) dimensions had a significant effect on behavioural intention to use AI.

2. To examine the mediating effect of superior functionality (SF) towards the relationship between technology readiness (TR) dimensions and behavioural intention to use AI.

3. To examine the mediating effect of perceived usefulness (PU) towards the relationship between technology readiness (TR) dimensions and behavioural intention to use AI.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Technology Readiness and Behavioural Intention in AI Utilization

In the realm of AI utilization, the synergy between Technology Readiness (TR) and Behavioural Intention (BI) forms a critical axis for understanding professional engagement with technological innovations. BI, rooted in the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), serves as a predictor of future behaviour, influenced by attitudes, subjective norms, and perceived behavioural control (Fishbein

& Ajzen, 1975). In technological contexts, the TAM further refined this concept, highlighting the role of individual attitudes and the perceived practicality of technology in shaping BI (Davis, 1989).

Simultaneously, as conceptualized by Parasuraman (2000), TR evaluates an individual's inclination towards new technologies. The Technology Readiness Index (TRI), with its multifaceted approach encompassing motivators and inhibitors, offers a comprehensive assessment of this readiness, integrating cognitive, emotional, and behavioural dimensions (Parasuraman & Colby, 2015). Contemporary research underscores the significance of these elements in shaping individual perceptions towards AI's functionality and pertinence (Kampa, 2023). The interplay between TR and BI significantly impacts accounting professionals, as their assessments of technology's utility and superiority notably influence BI (Venkatesh & Davis, 2000). This dynamic indicates that perceptions of AI's effectiveness, advanced functionality, and individual readiness crucially determine BI, outweighing the influence of societal norms (Gefen et al., 2003).

To effectively foster BI towards AI utilization, addressing both the enhancement of TR and the nurturing of favourable BI is imperative. As such, educational and professional strategies must focus on augmenting the technological skillset and cultivating an environment that supports and encourages proactive engagement with AI systems.

Technology Acceptance Model (TAM)

Originating from Davis (1989) as an evolution of the TRA, the TAM is renowned for its utility in discerning the determinants of technology utilization, with a particular emphasis on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). While traditionally, both constructs serve as pillars of the model, offering insights into users' BI, this study strategically focused on PU as the main internal factor due to its robust influence on the adoption decision-making process. The exclusion of PEOU is predicated on empirical evidence suggesting its impact on BI exhibits greater variability, leading to a decision to concentrate on the substantive benefits AI brings to accounting education rather than the operational ease (Venkatesh & Davis, 2000).

This study extended the TAM framework by including the Technology Readiness Index 2.0 (TRI 2.0) to examine individual differences—such as optimism, innovativeness, discomfort, and insecurity towards technology—and the system characteristic, Superior Functionality (SF). Incorporating personal attributes via the TRI 2.0 into the TAM unites user perception analysis with individual readiness evaluation. This fusion underscores the vital influence of personal traits on technology utilization, notably in AI, addressing TAM's limitations regarding implementation intentions and furnishing a detailed understanding of technology engagement drivers (Bryan Teoh Phern et al., 2024). The inclusion of system characteristic, SF, extended the model's scope to consider external technological attributes, thereby elucidating their influence on technology engagement in educational and professional settings. This approach enabled a more nuanced understanding of the determinants of technology acceptance, merging individual and system-level factors to predict usage intentions more accurately (Hong et al., 2002).

Optimism

Optimism (OP) plays a pivotal role in advancing TR by highlighting the potential of technology to enhance control, flexibility, and efficiency (Parasuraman, 2000). This view, grounded in cognitive psychology, promotes resilience and adaptability, envisaging technology as a key driver of innovation and transformative change. Parasuraman and Colby (2015) further elaborated that OP led to a positive appraisal of technology's impact on life quality. This perspective often regarded technology, especially AI, as surpassing traditional methods, thus fostering broader recognition and advocacy (Roy et al., 2018). Moreover, OP significantly influenced perceptions of sophisticated technologies, transforming the narrative from viewing these as mere tools to being integral in strategic achievements (Thompson et al., 1991). The TRA posits that attitudes significantly influence BI, suggesting that OP enhances perceptions of AI. In their Decomposed TPB, Taylor and Todd (1995) argued that OP strengthened technology usage intentions through positive attitudes and resilience. Thus, accounting students with optimistic traits, noted for adaptability and low avoidance behaviours, are predisposed to engage with technology, maintaining this inclination despite adverse information.

H1 (a): Optimism positively affects the superior functionality of AI.
H1 (b): Optimism positively influences the perceived usefulness of AI.
H1 (c): Optimism positively affects the behavioural intention to use AI.

Innovativeness

Innovativeness (IN), a key facet of TR, is marked by a proactive engagement with emerging technologies, going beyond mere interest to a strong drive for developing new technological solutions (Parasuraman & Colby, 2015). This quality is crucial in the early stages of AI integration, where innovative individuals play a pivotal role as trendsetters, deeply involved in harnessing the technology's potential and applying it to complex scenarios. Deci (1975)'s Intrinsic Motivation Theory posits that internal motivators such as curiosity are crucial for grasping AI's complexities and its transformative potential, underscoring that innovation-oriented individuals are adept at discerning technologies' advanced functionalities. IN significantly impacts PU, reflecting an attraction to novelty and a substantial cognitive engagement with technology's practical uses (Agarwal & Prasad, 1998). Individuals with high IN are early adopters, possessing a keen understanding of technology's applications, marked by risk-taking and proactive pursuit of knowledge. This depth of engagement shapes their assessments, rendering them discerning evaluators of technological potential (Lu et al., 2005). Rogers (2003) characterizes IN as a predisposition towards early integrating new technologies, correlating with positive technology engagement intentions. Notably, accounting students with pronounced IN, marked by boldness and curiosity, are inclined to explore emerging technologies, enhancing their comprehension and skilfulness (Hemdi et al., 2016). This proclivity for technological exploration fosters expertise in innovations and establishes these individuals as pioneers and influencers in AI-centric domains.

H2 (a): Innovativeness positively influences the superior functionality of AI.
H2 (b): Innovativeness positively impacts AI's perceived usefulness.
H2 (c): Innovativeness positively affects the behavioural intention to utilize AI.

Discomfort

Discomfort (DS) is a critical factor in TR, characterized by hesitations or anxieties in using modern technologies like AI, often stemming from past negative experiences or the complexities of technological interfaces (Parasuraman & Colby, 2015). DS manifests in a perceived lack of control and feeling overwhelmed, coupled with concerns over the inclusivity of technology-driven services and products. Moore and Benbasat (1991) elucidated that familiarity with technology fundamentally influences the acknowledgment of its SF; individuals more adept with technology are predisposed to identifying its superior attributes. Building on this, Ferreira et al. (2014) pointed out that an increased level of DS may introduce a negative bias, undermining the perceived effectiveness of modern technologies. This, in turn, significantly affected the evaluation of technology's utility, often leading to an overemphasis on perceived challenges and a consequent undervaluation of its potential value. Thus, DS presents a critical obstacle to technology engagement, fostering perceptions of complexity and lowering confidence, leading to avoidance and increased anxiety (Ramírez-Correa et al., 2019). This cautious approach often results in limited use and a preference for simpler solutions, restricting advanced technology use like AI.

H3 (a): Discomfort negatively impacts the superior functionality of AI.
H3 (b): Discomfort negatively affects AI's perceived usefulness.
H3 (c): Discomfort negatively influences the behavioural intention to use AI.

Insecurity

Insecurity (IS) encompasses deep-seated concerns about modern technologies stemming from apprehensions about reliability and safety. It is often rooted in a fundamental mistrust of their dependability and possible adverse effects (Parasuraman & Colby, 2015). This sentiment heightens fears of unauthorized access and data breaches, leading to the undervaluation of the capabilities of modern technologies— a significant concern in accounting due to the handling of sensitive data (Walczuch et al., 2007). Scepticism towards technological advancements serves to deter engagement with AI, undermining trust, attenuating the perceived utility of such technologies, and engendering resistance to their integration. The trepidation surrounding over-reliance and the non-fulfilment of anticipations further undermines user confidence, necessitating a circumspect utilization emphasising security and data integrity (Roberts et al., 2021). Moreover, within the discipline of accounting—where trust and interpersonal interactions are paramount—fears regarding technological dependency and the attenuation of client interactions present formidable obstacles to the embracement of AI by accounting students (Flavián et al., 2021).

H4 (a): Insecurity negatively impacts the superior functionality of AI.
H4 (b): Insecurity negatively influences AI's perceived usefulness.
H4 (c): Insecurity negatively affects the behavioural intention to use AI.

Superior Functionality

Drawing from Rogers (2003)'s Diffusion of Innovations Theory, Superior Functionality (SF) highlights the advantages new technologies like AI offer over traditional methods in accounting, notably in efficiency, adaptability, and predictive capabilities (Sun et al., 2020). AI's advancements align with the requisite skills for future accountants, significantly influencing students' BI to utilize AI due to its superior analytical and problem-solving abilities. The preference for AI, underscored by its relative advantage in areas such as predictive analytics and fraud detection (Riquelme & Rios, 2010), plays a critical role in student engagement and their inclination towards integrating AI in their academic and future professional practices.

H5: Superior functionality positively affects the behavioural intentions to use AI.

Perceived Usefulness

Perceived Usefulness (PU), central to the TAM by Davis (1989), significantly influences user attitudes and BI towards technology, emphasizing its effect on job performance enhancement. Empirical studies (Chang & Tung, 2007; Venkatesh & Bala, 2008) have highlighted PU as a critical determinant of technology use intentions, often outpacing Perceived Ease of Use (PEOU) in predicting user behaviour. In accounting education, PU significantly influences students' BI to integrate AI, recognizing the technology's potential to enhance professional skills and career prospects (Abdullah & Almaqtari, 2024). Such an influence highlights the crucial role of PU in evaluating functionality and acknowledging AI's strategic importance for task performance and analytical insights.

H6: Perceived usefulness positively affects the behavioural intentions to use AI.

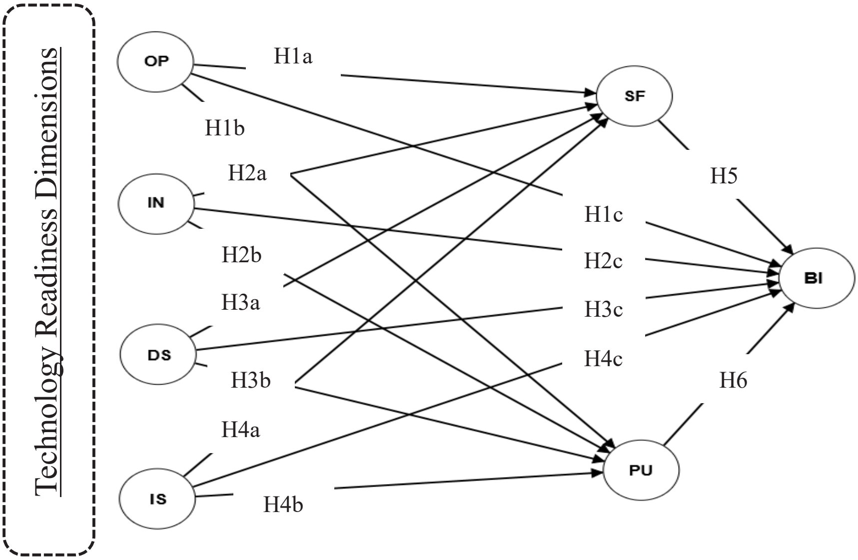

Figure 1: Conceptual Model of Behavioural Intention to Use AI

RESEARCH METHODOLOGY

This cross-sectional study, rooted in the positivist paradigm that prioritizes objective reality and scientific accuracy, adopted a survey methodology to facilitate quantitative analysis with empirical precision. This study focused on third and fourth-year undergraduate accounting students from four notable Malaysian universities: Universiti Malaya (UM), Universiti Kebangsaan Malaysia (UKM), Sunway University (SU), and Multimedia University (MMU). These institutions were selected for their excellence in accounting education and geographical diversity. UM and UKM are leading public universities known for their robust accounting programs and focus on technological research. In contrast, as private universities, SU and MMU are recognized for their technological emphasis and international academic partnerships. This diverse selection enabled a thorough analysis of students' perceptions of AI in accounting, contributing to an in-depth understanding of their BI.

Adopting a convenience sampling method, as Saunders et al. (2019) suggested, the study targeted approximately 1,244 students, aiming for a sample size of 294 based on a 95% confidence level and a 5% margin of error (Bryman & Bell, 2015). It achieved a 46.26% response rate from 136 students, aligning with the 30% to 50% social science norm (Bartlett et al., 2001) and adheres to Hair et al. (2016)'s ten-times rule for statistical soundness, ensuring the robustness of the study's findings.

For statistical analysis, SPSS was selected for its comprehensive analytical capabilities and intuitive interface, enabling nuanced descriptive and comparative analysis. In parallel, the application of SMART PLS 4, leveraging Partial Least Squares Structural Equation Modelling (PLS-SEM) and its advanced bootstrapping features, enhances the methodological rigour of this study. It facilitated comprehensive reliability and validity assessments of the structural models, allowing for examining both direct and indirect effects independent of conventional data distribution norms. Such methodological integration underlines the study's commitment to analytical depth, offering precise insights into accounting students' perceptions and intentions regarding AI technology.

Measurement of Variables

The survey was meticulously designed to ensure validity and reliability, collecting demographic information and a variety of constructs such as academic year, ethnicity, university affiliation, nationality, and gender. This approach supported the rigorous evaluation of psychological constructs pertinent to technology engagement within the accounting student population. TR is measured using a comprehensive 16-item scale from Parasuraman and Colby (2015), which delineated dimensions such as OP, IN, DS, and IS, enabling the exploration of students' diverse attitudes toward technology. For example, "New technologies contribute to a better quality of life" evaluates OP, whereas "Technology systems are not designed for use by ordinary people" assesses DS, thus reflecting a spectrum of technological attitudes. The SF of AI is assessed via a four-item scale, informed by the research of Orel and Kara (2014) and Wünderlich et al. (2013), concentrating on AI's distinctive capabilities beyond conventional methodologies. Respondents evaluated statements such as "AI system supports real-time communication in accounting" to determine the perceived advanced functionalities of AI within the accounting domain.

PU and BI towards AI usage were investigated using scales formulated by Davis (1989). PU was examined through six items, including "Using AI technologies would enhance my effectiveness in both academic and future roles in accounting," which appraises the impact of AI on job performance. Conversely, BI was gauged with three items, such as "I plan to use AI technologies in my future accounting role," reflecting the inclination towards future AI usage. These constructs are crucial for comprehending the motivational factors driving AI engagement. Participants provided their responses to each survey item on a 7-point Likert scale, ranging from Strongly Disagree (1) to Strongly Agree (7). This methodical rating process, combined with the judicious selection of survey items, enabled a detailed examination of student perspectives and intentions regarding AI.

Table 1: Measurement of Variables

Variables	Main Sources
Technology Readiness Dimensions (Optimism, Innovativeness, Discomfort, Insecurity)	Parasuraman and Colby (2015)
Superior Functionality	Orel and Kara (2014); Wünderlich et al. (2013)
Perceived Usefulness	Davis (1989)
Behavioural Intention to Use	Davis (1989)

RESULTS

Data Cleaning

The data cleansing of 138 survey responses led to the removal of two duplicates, leaving 136 unique responses. This included checks for straight-lining and outlier evaluation to maintain dataset authenticity and diversity.

Descriptive Analysis

The study primarily involved third-year students (61.8%), with fourth-year students less represented (38.2%), attributed to their rigorous coursework and SU's three-year accounting program. Among the universities, UM led in participation (29.4%), followed by MMU at 27.9%, UKM at 24.3%, and SU at 18.4%, showcasing a balanced mix of private (46.3%) and public (53.7%) institutions. Ethnically, the respondents were

58.1% Chinese, 25% Malay, and 16.9% Indian, indicative of the accounting programs' demographics. Predominantly, Malaysian participants (98.5%) marked a slight deviation from the increasing interest of international students. Female respondents (75.7%) significantly outnumbered males, reflecting gender distributions within the accounting faculties and broader educational patterns.

Table 2: Demographic Profiles of The Respondents

Items		Frequency	Percentage
Academic Year	Year 3	84	61.8
	Year 4	52	38.2
University	Universiti Malaya (UM)	40	29.4
	Universiti Kebangsaan Malaysia (UKM)	33	24.3
	Sunway University (SU)	25	18.4
	Multimedia University (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

N=136

The study showed a nuanced understanding of students' perceptions of AI across public and private institutions in Table 3. Private university attendees demonstrated greater DS (3.61 vs. 3.00) and IS (5.13 vs. 4.95), reflecting increased AI risk concerns. However, OP and IN levels were similarly high across both cohorts, with public students marginally leading (OP: 5.85, IN: 4.82) compared to private (OP: 5.74, IN: 4.66), suggesting a collective optimism about AI. BI towards AI usage was notably stronger among public students (6.32 mean) than private (5.98 mean). PU and SF were equally recognized, with matching PU scores (5.99) and proximate SF scores (public: 5.81, private: 5.57), highlighting a consensus on AI's utility. Despite varying DS and IS, both groups exhibited a uniformly positive AI outlook, evidenced by shared OP, IN, and a recognition of its academic and professional value.

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

Constructs	Public Universities (UM, UKM)	Private Universities (SU, MMU)
	Mean	
Optimism (OP)	5.85	5.74
Innovation (IN)	4.82	4.66
Discomfort (DS)	3.00	3.61
Insecurity (IS)	4.95	5.13
Perceived Usefulness (PU)	5.99	5.99
Superior Functionality (SF)	5.81	5.57
Behavioural Intention (BI) to use	6.32	5.98

Measurement Model

In PLS-SEM analysis, evaluating the measurement model's reliability and validity is crucial to ensure data dependability and accurate results, thereby confirming the consistency and precision of outcomes (Mohajan, 2017). The research verified convergent validity, with all Average Variance Extracted (AVE) values surpassing 0.5, signifying robust construct representation, as detailed in Table 5. Outer loading values were pivotal for evaluating indicator strength, considering values above 0.70 signified a strong association, whereas those ranging from 0.4 to 0.7 were deemed moderate. Indicators scoring below 0.4, such as the IS4 item in the Insecurity (IS) dimension with a value of 0.18, denoted a weak association and necessitate removal, as delineated in Table 4.

Collinearity detection, crucial for model clarity, highlights significant correlations among indicators, potentially masking individual effects. The Variance Inflation Factor (VIF) assesses collinearity with values above 5, suggesting considerable distortion in coefficient variance, resulting in unreliable estimates. For accuracy and rigor, constructs like BI2 and PU2, exhibiting high VIF values, as shown in Table 4, were excluded from the analysis to prevent interpretative errors and uphold model integrity.

Table 4: Outer Loadings (Mean, Standard Deviation, T-Values) and Collinearity Statistics (VIF)

Items	Original sample	Sample mean (M)	Standard deviation	T statistics	VIF
BI1	0.947	0.946	0.013	72.963	4.741
BI2	0.955	0.955	0.008	113.996	5.117
BI3	0.897	0.898	0.028	31.84	2.721
PU1	0.858	0.856	0.03	28.633	3.485
PU2	0.908	0.906	0.022	41.751	5.102
PU3	0.903	0.903	0.017	51.975	4.354
PU4	0.909	0.909	0.021	43.497	4.222
PU5	0.894	0.895	0.023	39.594	4.189
PU6	0.872	0.87	0.029	29.993	3.076
SF1	0.822	0.821	0.046	17.983	1.739
SF2	0.812	0.811	0.031	26.219	1.759
SF3	0.842	0.844	0.036	23.13	2.118
SF4	0.795	0.792	0.047	16.929	1.847
DS1	0.827	0.816	0.072	11.56	2.097
DS2	0.846	0.838	0.069	12.355	2.611
DS3	0.889	0.881	0.051	17.571	3.069
DS4	0.93	0.924	0.04	23.019	3.662
IN1	0.771	0.766	0.056	13.788	1.835
IN2	0.803	0.801	0.041	19.726	1.961
IN3	0.783	0.78	0.05	15.79	1.578
IN4	0.834	0.835	0.032	25.824	1.584
OP1	0.832	0.825	0.043	19.345	2.381
OP2	0.826	0.819	0.044	18.889	2.390
OP3	0.731	0.734	0.048	15.157	1.595
OP4	0.804	0.804	0.036	22.187	1.793
IS1	0.854	0.826	0.102	8.352	1.533
IS2	0.828	0.818	0.092	9.007	1.557
IS3	0.776	0.749	0.107	7.286	1.792
IS4	0.180	0.154	0.216	0.831	1.101

The study evaluated internal consistency reliability through Cronbach's alpha and composite reliability, assessing the coherence among items within a construct on a scale from 0 to 1, where higher values indicate greater reliability. Adhering to Nunnally (1978), the constructs demonstrate high reliability, achieving Cronbach's alpha and composite reliability scores, including rho_a and rho_C, of 0.7 or above, as presented in Table 5.

Table 5: Cronbach's Alpha, Composite Reliability and AVE

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.926	0.935	0.953	0.953
DS	0.898	0.967	0.928	0.928
IN	0.814	0.845	0.875	0.875
IS	0.772	0.809	0.863	0.863
OP	0.811	0.815	0.876	0.876
PU	0.948	0.948	0.958	0.958
SF	0.835	0.839	0.890	0.890

Discriminant validity, essential for ensuring construct distinctiveness, was confirmed using cross-loadings, the Fornell-Larcker criterion, and HTMT ratio analysis. Cross-loadings demonstrated that items load more significantly on their intended constructs, surpassing Hair et al. (2011) 0.7 benchmark for construct differentiation (Table 6). The Fornell-Larcker criterion was met as each construct's AVE square root exceeds its correlations with other constructs, confirming its unique representation (Table 7). Additionally, the HTMT ratio, in line with Henseler et al. (2014) standards, showed all values below the 0.85 threshold, further validating the distinctness of the constructs (Table 8).

Table 6: Cross Loadings

Items	BI	PU	SF	DS	IN	OP	IS
BI1	0.947	0.489	0.644	-0.198	0.364	0.453	0.332
BI2	0.955	0.513	0.664	-0.196	0.408	0.51	0.309
BI3	0.897	0.493	0.538	-0.24	0.307	0.384	0.198
PU1	0.505	0.858	0.549	-0.189	0.255	0.422	0.153
PU2	0.458	0.908	0.583	-0.092	0.339	0.47	0.26
PU3	0.43	0.902	0.591	-0.12	0.315	0.452	0.309
PU4	0.449	0.909	0.568	-0.091	0.319	0.435	0.213
PU5	0.511	0.894	0.601	-0.089	0.326	0.43	0.26
PU6	0.493	0.872	0.574	-0.096	0.301	0.491	0.292
SF1	0.597	0.566	0.823	-0.031	0.463	0.461	0.276
SF2	0.557	0.54	0.811	-0.08	0.442	0.459	0.27
SF3	0.514	0.439	0.842	-0.081	0.382	0.393	0.318
SF4	0.487	0.576	0.795	-0.108	0.372	0.344	0.269
DS1	-0.189	-0.049	-0.119	0.827	-0.059	-0.17	-0.039

DS2	-0.124	-0.094	-0.017	0.846	-0.053	-0.093	0.109
DS3	-0.154	-0.149	-0.04	0.889	0.014	-0.157	0.186
DS4	-0.268	-0.138	-0.105	0.93	-0.025	-0.133	0.089
IN1	0.216	0.231	0.33	0.023	0.771	0.395	0.186
IN2	0.288	0.106	0.394	0.057	0.803	0.383	0.151
IN3	0.257	0.282	0.414	0.078	0.783	0.216	0.201
IN4	0.424	0.416	0.465	-0.188	0.834	0.552	0.415
OP1	0.459	0.425	0.433	-0.057	0.299	0.832	0.417
OP2	0.385	0.353	0.398	-0.167	0.358	0.826	0.347
OP3	0.299	0.433	0.37	-0.153	0.451	0.731	0.282
OP4	0.391	0.406	0.428	-0.144	0.498	0.804	0.27
IS1	0.268	0.341	0.31	0.089	0.296	0.421	0.857
IS2	0.266	0.208	0.31	0.039	0.23	0.318	0.826
IS3	0.197	0.061	0.205	0.128	0.276	0.238	0.786

Table 7: Fornell–Larcker Criterion

Constructs	BI	DS	IN	IS	OP	PU	SF
BI	0.934						
DS	-0.224	0.874					
IN	0.388	-0.033	0.798				
IS	0.303	0.095	0.323	0.823			
OP	0.484	-0.160	0.499	0.414	0.799		
PU	0.534	-0.126	0.348	0.279	0.506	0.891	
SF	0.662	-0.089	0.511	0.346	0.511	0.649	0.818

Table 8: Heterotrait-Monotrait (HTMT) Ratio

Constructs	BI	DS	IN	IS	OP	PU	SF
BI							
DS	0.249						
IN	0.404	0.147					
IS	0.336	0.155	0.375				
OP	0.528	0.189	0.598	0.496			
PU	0.586	0.138	0.362	0.295	0.575		
SF	0.735	0.103	0.601	0.414	0.614	0.731	

Structural Model

Table 9 demonstrates that the R-square values for the study's constructs indicate their explanatory power, consistent with established benchmarks. Behavioural Intention (BI) has an R-square of 0.464, reflecting a moderate explanatory level as defined by Falk and Miller (1992). Perceived Usefulness (PU) and Superior Functionality (SF) exhibited R-squares of 0.270 and 0.362, respectively, aligning with a moderate explanatory scope. While the model accounted for significant variance in these constructs, unexplained variance highlighted the need for further investigation into technology engagement.

Table 9: Structural Model (R-Square)

Items	R-square	R-square adjusted
BI	0.464	0.439
PU	0.270	0.248
SF	0.362	0.343

DISCUSSION

This study employed the bootstrapping technique through SMART PLS 4, as detailed in Table 10, to assess the model's direct effects through path coefficients and p-values. To complement these findings, specific indirect effects, focusing on the mediating roles of SF and PU across different dimensions, were also examined as shown Table 11. The subsequent analysis methodically examined the direct and indirect effects of each construct.

Table 10: Results of Testing Hypotheses (Direct Effects)

Relationship	β	T-Statistics	P values	Decision
$H_{1a:}$ OP → SF	0.290	2.895	0.004	Supported
$H_{1b:}$ OP → PU	0.403	4.153	0.000	Supported
$H_{1c:}$ OP → BI	0.119	1.034	0.124	Not Supported
$H_{2a:}$ IN → SF	0.324	3.884	0.000	Supported
$H_{2b:}$ IN → PU	0.118	1.272	0.145	Not Supported
$H_{2c:}$ IN → BI	0.016	0.102	0.850	Not Supported
$H_{3a:}$ DS → SF	-0.044	0.59	0.540	Not Supported

$H_{3b:}$ DS → PU	-0.066	0.996	0.404	Not Supported
$H_{3c:}$ DS →BI	-0.153	2.54	0.009	Supported
$H_{4a:}$ IS → SF	0.125	1.46	0.142	Not Supported
$H_{4b:}$ IS → PU	0.08	0.859	0.359	Not Supported
$H_{4c:}$ IS → BI	0.064	0.851	0.403	Not Supported
$H_{5:}$ SF → BI	0.480	4.668	0.000	Supported
$H_{6:}$ PU → BI	0.119	1.082	0.315	Not Supported

Table 11: Specific Indirect Effects

Relationships	β	T-Statistics	P values	Indirect/ Mediation
OP → SF → BI	0.139	2.484	0.015**	Full
OP → PU → BI	0.048	0.967	0.374	No
IN → SF → BI	0.156	2.728	0.005**	Full
IN → PU → BI	0.014	0.754	0.452	No
DS → SF → BI	-0.021	0.572	0.547	No
DS → PU → BI	-0.008	0.641	0.592	No
IS → SF → BI	0.060	1.361	0.155	No
IS → PU → BI	0.009	0.623	0.538	No

The study corroborated that OP significantly affected AI's SF ($\beta = 0.290$, $p < 0.05$), affirming Hypothesis 1a in accordance with Roy et al. (2018), indicating that OP enhanced recognition of AI's advanced professional capabilities. Furthermore, OP positively impacted PU of AI ($\beta = 0.403$, $p < 0.05$), endorsing Hypothesis 1b and echoing findings by Kampa (2023) and Yusuf et al. (2021), indicative of students' confidence in AI's value for accounting. Nonetheless, the link between OP and BI to utilize AI did not reach statistical significance ($\beta = 0.093$, $p > 0.05$), suggesting that OP alone might not propel the intent to employ AI, thus rejecting Hypothesis 1c in line with Negm (2022). SF served as a full mediator in linking OP with BI towards AI, highlighting the perception of AI's superiority ($\beta = 0.139$, $p < 0.05$), while the mediating role of PU was minimal ($\beta = 0.048$, $p > 0.05$), reflecting a limited practical understanding of AI. This indicated that the broad capabilities of AI significantly swayed students' OP beyond their granular grasp of its applications in accounting.

The study identified a significant positive link between IN and the SF of AI ($\beta = 0.324$, $p < 0.05$), validating Hypothesis 2a and resonating with Agarwal and Karahanna (2000). Conversely, the connection between IN and PU was not significant ($\beta = 0.118$, $p > 0.05$), thereby not supporting Hypothesis 2b, in line with Kampa (2023). These results suggested that while students recognized AI's potential, they did not view its current implementations in accounting as fully meeting their needs. Such a perspective highlights a blend of enthusiasm for innovation with a realistic assessment of technology's utility in accounting. Furthermore, the study found no significant association between IN and BI to use AI ($\beta = 0.016$, $p > 0.05$), challenging Hypothesis 2c and corresponding with findings by Flavián et al. (2021) and Blut and Wang (2019), suggesting that IN, in isolation, does not catalyse the integration of AI into accounting education. Significantly, SF was found to fully mediate the relationship between IN and BI towards AI usage in accounting ($\beta = 0.156$, $p < 0.05$), affirming Agarwal and Prasad (1998). This result suggested that the primary driver of students' engagement intent with AI stems from their perception of its advanced capabilities, as opposed to its PU, which exhibited no significant mediating role ($\beta = 0.014$, $p > 0.05$). Such findings underscore a predilection for AI's distinctive attributes over its immediate practical utility within the accounting domain.

The analysis within the TR framework indicated that DS did not significantly impact perceptions of AI's SF ($\beta = -0.044$, $p > 0.05$), aligning with Lin et al. (2022) and not supporting Hypothesis 3a. Furthermore, DS's negative association with PU was not statistically significant ($\beta = -0.066$, $p > 0.05$), failing to confirm Hypothesis 3b and indicating that technological unease does not markedly affect cognitive evaluations of AI's utility. However, a significant negative correlation was observed between DS and the BI to use AI ($\beta = -0.153$, $p < 0.05$), corroborating Hypothesis 3c and echoing Negm (2022). This underscored that DS, fuelled by concerns over AI's complexity and perceived implications, directly diminished willingness to utilize AI. Neither SF ($\beta = -0.021$, $p > 0.05$) nor PU ($\beta = -0.008$, $p > 0.05$) significantly mediated the DS-BI relationship, suggesting that DS's impact on AI usage intentions was primarily driven by intrinsic apprehensions about the technology rather than its superior functionalities or utility.

The study uncovered a nuanced interaction between IS and AI attributes, characterized by positive but statistically insignificant correlations, necessitating the dismissal of Hypotheses 4a, 4b, and 4c. The associations between IS and both SF ($\beta = 0.125$, $p > 0.05$) and PU ($\beta = 0.08$, $p > 0.05$) did not substantially impact the recognition of AI's capabilities or its utility, consistent with findings by Yusuf et al. (2021). Moreover, the link between IS and BI to use AI ($\beta = 0.064$, $p > 0.05$) lacked significant influence on usage intentions, with neither SF ($\beta = 0.060$, $p > 0.05$) nor PU ($\beta = 0.009$, $p > 0.05$) demonstrating notable mediating effects. These outcomes suggested a context where IS coexists with an acknowledgment, or possibly a rudimentary awareness, of AI's potential, indicating a restricted understanding of AI and leading to neutral, inconsequential attitudes toward its integration. This highlights the imperative for more detailed research to decipher the intricate dynamics of these relationships.

The study established a significant positive correlation between SF of AI and BI to use it ($\beta = 0.48$, $p < 0.05$), corroborating Hypothesis 5 and echoing findings from Lu et al. (2014) and Lee et al. (2003). This finding demonstrated that for accounting students, AI's enhanced capabilities and superiority, such as processing large datasets and executing complex calculations, significantly swayed their intent to use AI over traditional methods. Hence, it emphasized the critical role of AI's advanced functionalities in fulfilling the professional and educational requirements within the accounting domain. The study found a statistically insignificant correlation between PU of AI technology and BI to use AI among accounting students ($\beta = 0.119$, $p > 0.05$), consistent with findings by Lin et al. (2007) and Buyle et al. (2018). The swift advancement of AI, combined with curricular gaps and limited exposure, could impede students' grasp of its consistent PU, influencing their usage intentions. Hence, bolstering AI integration in accounting education is key to enhancing the PU-usage intention link.

Implications

This study highlights the significant implications for stakeholders in accounting education, focusing on the roles of academic institutions and curriculum developers. It emphasizes the necessity of incorporating AI-focused content and competencies into accounting curricula and addressing factors that enhance students' engagement and intention to use AI. The research advocates for continuous curricular updates in response to the rapidly evolving technological landscape, ensuring that graduates possess both proficiency in relevant technologies and a comprehensive understanding of their extensive implications on business practices, regulatory frameworks, and financial reporting. Integrating AI into academic syllabi significantly enhances graduates' employability, making them vital for AI's strategic application in professional settings. This effort focuses on cultivating accounting professionals who are technically proficient, ethically attentive, and committed to social responsibility. Such professionals are equipped to contribute substantially to their organizations and the broader societal and economic systems, potentially spurring global innovation and reinforcing ethical practices.

CONCLUSION

This investigation, leveraging an extended Technology Acceptance Model (TAM), revealed key factors influencing accounting students' intention to engage with AI, drawing on data from 136 undergraduates across four Malaysian universities. The findings highlighted the critical roles of optimism, innovativeness, discomfort, and superior functionality in shaping students' AI usage intentions, advocating for a strategic overhaul of university accounting curricula to emphasize AI's superior functionality. Recommended actions include integrating case studies and simulations showcasing AI's applications in accounting and fostering an educational milieu that supports AI integration through innovation labs, technology competitions, and hands-on training with AI software and data analytics. The study suggests gradually introducing AI topics, counselling, and mentorship programs to mitigate students' AI discomfort. It emphasizes the critical need for continuous curricular adaptation to technological advancements, identifying key factors influencing students' intentions to engage with AI in accounting education. These insights facilitate the strategic integration of AI-focused curricula, preparing students for careers interwoven with AI.

Nevertheless, this study presented limitations, primarily due to its concentration on Malaysian accounting undergraduates, further accentuated by variances in accounting program architectures. These limitations underline the necessity for subsequent research to broaden its scope, including more diverse and larger samples, and to explore novel and less examined variables. Such expansion will enhance the research's relevance and accuracy, providing a more comprehensive understanding of the factors influencing students' intentions to use AI in accounting.

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