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Identifying NCA for Artificial Intelligence in Accounting and Auditing: Evidence from TAM and TPB Models

Abstract. *This study examines the factors that influence students' acceptance of artificial intelligence (AI) in accounting education. The data are investigated utilising a combined framework established on TAM and TPB. PLS-SEM analysis and a Necessary Conditions Analysis (NCA) were used to evaluate PU, PEU, ATT, and SN.*
The outcomes demonstrate that PU and PEU significantly affect ATT toward AI, as evidenced by their intentions to adopt AI tools for accounting. Additionally, students' perceptions of AI technologies are influenced by social norms (SN), which they receive from peers and teachers. In addition to contributing to a better understanding of how technology is adopted in educational contexts, the study offers valuable insights into instructional innovation and strategies that can enhance the relevance of accounting education during digital transformation. The implications of these findings are discussed, emphasising the need for educational programmes to adapt to the changing demands of the accounting profession.

Keywords: *artificial intelligence, digital transformation, TPB, TAM, necessary condition analysis.*

JEL Classification: M41, C55, O33.

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1. Introduction

The rapid evolution of technology continues to transform the global business landscape, compelling higher education to adapt accordingly. With technologies such as artificial intelligence (AI), blockchain, and data analytics now central to accounting and auditing practices, traditional curricula are increasingly misaligned with industry needs. Despite their proven potential to enhance accuracy and efficiency (Damerji & Salimi, 2021), these innovations are often absent from accounting education, which remains heavily theory-based and leaves graduates ill-equipped for a digitalised profession (Hasan et al., 2025).

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This gap between academic preparation and market demands has led to calls for curriculum reform that embeds relevant technological competencies (Chang & Nen-Chen, 2003; Cory & Pruske, 2012; Stoner, 2009). However, integrating technology into the classroom presents challenges, including student resistance, lack of confidence, and insufficient pedagogical support. Even digital natives may struggle to engage with new tools, underscoring the need to better understand the factors influencing student acceptance of technological innovations in accounting education.

To address this need, the present study examines the factors influencing students' acceptance of AI in accounting and auditing education. Drawing on the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), it investigates the influence of perceived usefulness (PU), perceived ease of use (PEU), attitude toward technology (ATT), and subjective norms (SN) on students' intention to adopt AI-based learning tools (Davis, 1989; Ajzen, 2020). Although these constructs are well-established in technology adoption literature, empirical research in accounting education remains limited.

This study offers both theoretical and practical contributions. Theoretically, it extends the application of the Theory of Acceptance and Use of Technology (TAM) and the Technology Acceptance Model (TRM) in a discipline-specific context. Practically, it provides evidence-based insights for educators, curriculum developers, and policymakers to support the effective integration of AI into accounting programmes. The findings aim to inform pedagogical strategies that align education with the skills required in a data-driven profession.

A dual-method approach is employed, utilising Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine relationships among key constructs and Necessary Condition Analysis (NCA) to identify non-negotiable conditions for AI acceptance (Dul, 2020). This rigorous methodology enables a nuanced analysis of both sufficiency and necessity.

Ultimately, this research contributes to the broader discourse on educational innovation by offering empirical guidance for embedding AI into accounting curricula. It enhances understanding of the psychological and social factors influencing technology adoption, supporting the development of education models that prepare students for a technology-driven economy.

2. Literature review

2*.1 Theoretical background*

The Technology Acceptance Model (TAM) (Davis, 1989) and the Theory of Planned Behaviour (TPB) (Ajzen, 2020) are widely used to examine mobile learning adoption and behavioural intentions. However, the growing complexity of technology integration in education, particularly in the field of artificial intelligence (AI), necessitates the inclusion of additional variables to enhance explanatory power (Malik et al., 2019).

Integrating perceived usefulness (PU) and perceived ease of use (PEU) into the Theory of Planned Behaviour (TPB) has been shown to strengthen its predictive capacity (Lazea et al., 2024). In higher education, the PEU reflects the ease with which students can achieve learning outcomes (Lazea et al., 2024). The alignment of TAM and TPB in explaining attitudes and behavioural intentions supports their combined application (Chen & Chao, 2011).

While early studies primarily explored the functional aspects of AI, its integration in education signals a pedagogical shift rather than the adoption of a mere tool. The habitual use of platforms like WhatsApp in academic contexts illustrates how habit contributes to the sustained use of mobile learning technologies (Malik et al., 2019; Chen & Chao, 2011).

TAM remains a cornerstone in information systems research, including among accounting students, where it is used to analyse the link between key factors and behavioural intention (Damerji & Salimi, 2021). The model has evolved to incorporate constructs such as attitude toward technology (ATT) and subjective norms (SN), offering a broader understanding of user behaviour.

Recent studies also highlight the need to investigate how previous usage influences future behavioural intentions. As technology becomes increasingly embedded in daily routines, the impact of habit may diminish (Aljasimee et al., 2019). In response, the theoretical model proposed in this study (see Figure 1) integrates the Theory of Planned Behaviour (TPB) and the concept of habit to provide a comprehensive framework for understanding AI acceptance and continued use in accounting education.

2.2 Hypothesis generation

2.2.1 The Impact of Perceived Usefulness (PU) on technology adoption

Perceived usefulness (PU) refers to the extent to which individuals believe that a specific technology will enhance their performance (Al Jasimee & Blanco-Encomienda, 2024). Within the Technology Acceptance Model (TAM), PU is a key predictor of behavioural intention, influencing the likelihood of technology adoption. Prior studies have consistently demonstrated a positive relationship between PU and the adoption of artificial intelligence (AI) in education (e.g., Joo et al., 2017; Damerji & Salimi, 2021).

In the context of accounting and auditing education, PU reflects students' perceptions of the value of learning about AI. Technologies such as AI can automate routine tasks, enhance financial analysis, and provide real-time insights, thereby improving professional efficiency and decision-making.

Attitudes towards innovation are strongly shaped by both perceived usefulness and perceived ease of use (Davis et al., 1989). PU is influenced not only by expected performance benefits, but also by how easily a technology can be used. Empirical studies confirm that ease of use positively affects perceived usefulness, suggesting a reinforcing relationship between the two constructs. TAM has proven to be a robust framework across various contexts, with PU consistently emerging as a critical factor in shaping user acceptance (Sugandini et al., 2017).

Given the consistently positive empirical findings, the following proposition is put forward:

H1: Perceived usefulness is a necessary component of Technology Adoption (TA).

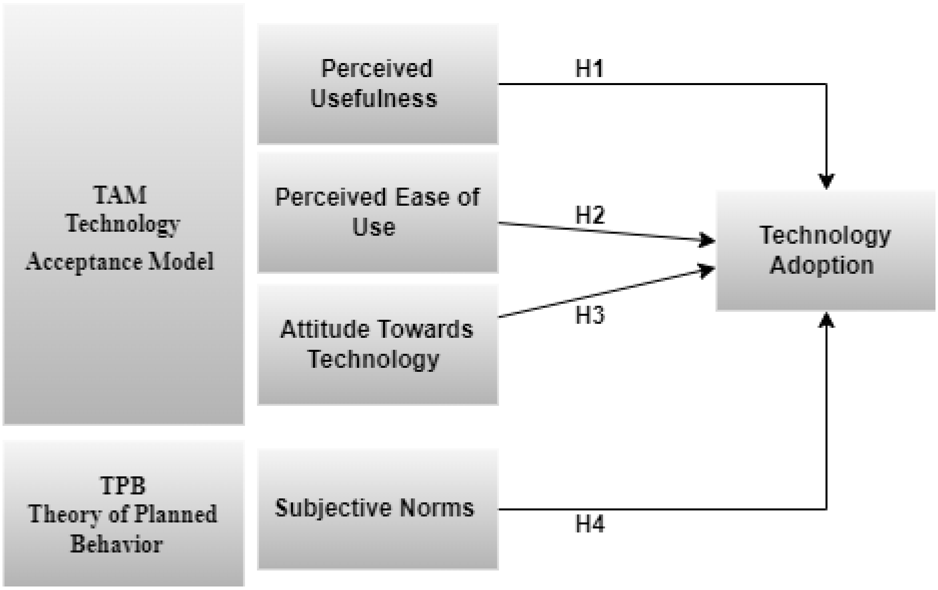

Figure 1. Conceptual model
Source: Authors' own creation.

2.2.2 The Impact of perceived ease of use (PEU) on technology adoption

Perceived ease of use (PEU) is a foundational construct within the Technology Acceptance Model (TAM), referring to the degree to which users believe that a technology is simple to use and requires minimal effort (Davis et al., 1989). When a system is perceived as intuitive and user-friendly, individuals are more likely to adopt it. Numerous studies have confirmed the positive association between ease of use and technology adoption, both generally (e.g., Joo et al., 2017) and specifically in relation to artificial intelligence (AI) (Damerji & Salimi, 2021).

This perception becomes especially critical when introducing complex technologies such as AI to students. Their sense of ease is shaped not only by the usability of AI tools but also by their ability to understand and apply AI concepts in practical accounting scenarios. Clear, well-structured learning materials and intuitive platforms reduce cognitive load, making AI more approachable and boosting learners' confidence (Davis et al., 1989).

When tools are accessible and require little training, students are more inclined to explore AI's potential. This fosters positive engagement and reinforces the perception of AI as a valuable and manageable domain. Ultimately, when AI is seen as easy to learn and use, it encourages adoption and may positively influence students' future career readiness in the accounting profession (Joo et al., 2017; Davis et al., 1989). Accordingly, the following proposition is advanced:

H2: Perceived ease of use constitutes a necessary component in Technology Adoption (TA)

2.2.3 The Impact of attitude towards technology on technology adoption

Attitudes toward medical technology reflect an individual's general stance – whether supportive or resistant – towards its use (Jan & Contreras, 2011). However, attitude is not merely a general feeling; it encompasses emotional and cognitive responses that shape a person's willingness to engage with technology.

Teo and Wong (2013) stress the importance of exploring learners' attitudes, emotions, and intentions regarding medical technologies. Within the Technology Acceptance Model (TAM), attitude (ATT) represents a user's evaluation of a technology, influenced by beliefs, emotions, and behavioural intentions (Davis et al., 1989). Positive attitudes are often linked to greater perceived usefulness and ease of use, increasing motivation to adopt technology. In contrast, negative attitudes – driven by perceptions of complexity or irrelevance – may lead to resistance (Teo & Wong, 2013).

In the context of AI, ATT significantly influences users' openness and readiness. A favourable attitude can make AI tools seem more accessible and valuable, while a negative one may lead to apprehension and limited engagement. Research confirms that students' perceptions of a technology's usefulness strongly shape their attitudes (Teo & Wong, 2013).

Jan and Contreras (2011) describe attitude as an emotional response to technology, which in self-directed learning settings, directly impacts student engagement. According to TAM, perceived usefulness and ease of use are core predictors of attitude, which subsequently affects behavioural intention and actual usage (Davis et al., 1989). This highlights the central role of attitude in fostering successful technology integration within education.

H3: Attitude toward technology (ATT) is a necessary component in the Technology Adoption (TA).

2.2.4 The Impact of subjective norms on technology adoption

Subjective norms (SN) refer to perceived social pressures influencing an individual's technology adoption. These may originate from peers, mentors, educators, or industry professionals, who can support or discourage adoption (Jan & Contreras, 2011). Both the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) recognise SN as a key predictor of behavioural intention (Teo & Wong, 2013).

Empirical studies show a positive link between SN and technology adoption. Individuals are more likely to adopt a technology when they perceive approval from influential others (Mayakol, Kiyatsin & Prasad, 2018). In healthcare, for example, social endorsement significantly shapes attitudes toward new technologies (Teo & Wong, 2013).

In culturally sensitive contexts, SN become even more influential. Social acceptance or rejection – often shaped by cultural norms – can determine whether healthcare professionals adopt or resist innovation (Damerji & Salimi, 2021; Zia, Shahin & Sardar, 2018).

In accounting and auditing education, students' perceptions of how peers, instructors, and professionals view AI can powerfully affect their attitudes and intentions. Support from respected figures increases perceived value, while scepticism may hinder adoption (Joo et al., 2017).

The Social Networks Extension of the Technology Acceptance Model (TAM) further emphasises the impact of social support on adoption (Davis et al., 1989). In professional education, the views of authority figures and peers are critical in shaping students' behavioural intentions. Thus, subjective norms play a vital role in encouraging AI integration and fostering a culture of innovation in accounting education (Jan & Contreras, 2011).

H4: Subjective Norms (SN) are necessary for components in the Technology Adoption (TA).

3. Method

3.1 Participants

This study surveyed 760 students enrolled in undergraduate and postgraduate accounting and auditing programmes across 11 Spanish universities. Of the 760 questionnaires distributed, 650 were returned, yielding a response rate of 85.5%. After data screening, 571 responses were deemed valid for analysis.

The participants came from diverse academic backgrounds, all of which included auditing courses within their curricula. Of the total respondents, 295 students indicated an interest in pursuing a career in auditing. This subgroup comprised 34% female and 66% male students, reflecting the gender diversity. A majority of the sample (62%) were aged under 24, while 38% fell within the 25–44 age range, highlighting a broad age distribution. Additionally, 23% of respondents reported prior professional experience in accounting or auditing, further contributing to the heterogeneity of the sample.

3.2 Sampling Strategy and Research Design

The study employed a cross-sectional quantitative research design, which is appropriate for examining technology acceptance constructs at a single point in time.

A multi-stage sampling strategy was used to ensure coverage across different academic contexts.

At the initial stage, 11 Spanish universities offering accounting and auditing programmes with exposure to digital or AI-related content were purposively selected.

During the second stage, participants were recruited through convenience sampling within each institution, with course instructors distributing the questionnaire to eligible students. This approach highlights the importance of participants' involvement, fostering appreciation for their contributions to the study's success.

A pilot test involving 32 respondents was conducted to improve item clarity and verify measurement reliability, thereby enhancing the overall data quality before full dataset collection.

To ensure data quality, evaluation techniques estimated missing values, specified multivariate outliers, and evaluated potential common-method bias (Al-Daoud & Abu-AlSondos, 2025). Harman’s single-factor test showed that no single factor accounted for the most variance, indicating a low risk of common method bias in the dataset.

This sampling strategy and research design provided a robust foundation for analysing the determinants of AI acceptance in accounting education.

3.3 Research instrument

A quantitative approach was employed, using a structured questionnaire developed based on the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), with the intention to adopt AI considered as an external variable. The questionnaire comprised two sections: the first collected demographic information, while the second measured four core constructs, perceived usefulness (PU), perceived ease of use (PEU), attitude toward technology (ATT), and subjective norms (SN).

Each construct was measured using a 7-point Likert scale ranging from 'Strongly disagree' (1) to 'Strongly agree' (7). Following Davis (1989), PU and PEU were each assessed using six items, ATT with three items, and SN with three indicators. Technology adoption (TA) intention was measured using two items, along with a single item adapted from Damerji and Salimi (2021), assessing students’ interest in enrolling in a course on AI applications in accounting.

3.4 Data analysis

To address the research objectives, a dual analytical approach was adopted. Necessary Condition Analysis (NCA) was conducted using the NCA package in R, and Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed to estimate latent construct values, following established procedures in the literature (Hair et al., 2020).

NCA was applied to determine whether the dimensions of the Technology Acceptance Model (TAM) serve as necessary conditions for technology adoption (TA). Rooted in necessity logic, NCA posits that certain outcomes cannot be achieved unless specific conditions are present; these necessary conditions cannot be substituted or compensated by other variables (Dul, 2020). This method highlights the strategic relevance of TAM constructs in achieving the desired adoption outcomes.

Scatter plots were used to identify ceiling lines, allowing the evaluation of necessity relationships. NCA estimates two key parameters: ceiling accuracy (c-accuracy), indicating the percentage of observations above or below the ceiling line, and the effect size of necessity, reflecting the strength of each construct as a bottleneck for the outcome.

4. Results

4.1 Measurement model

As a preliminary step to hypothesis testing, Confirmatory Factor Analysis (CFA) was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) (see Table 1). In line with Hair et al. (2020), all indicator loadings exceeded the recommended threshold of 0.50, indicating acceptable item reliability.

Construct reliability was further supported by Rho-A, Composite Reliability (Rho-C), and Cronbach's alpha values, all of which surpassed the 0.70 threshold (Dul, 2020). Moreover, the Average Variance Extracted (AVE) values were above 0.50 for all constructs, confirming convergent validity and indicating that each construct explained more than half of the variance of its indicators (Hair et al., 2020).

Table 1. Validity and reliability of the constructs

Construct/Item	Item Loading	VIF	Alpha	Rh-A	Rh-C	AVE
Perceived Usefulness (PU)						
PU1	0.757	1.623	0.823	0.824	0.872	0.531
PU2	0.744	1.716				
PU3	0.720	1.630				
PU4	0.725	1.730				
PU5	0.749	1.737				
PU6	0.674	1.335				
Perceived Ease of Use (PEU)						
PEU1	0.792	1.996	0.887	0.889	0.914	0.639
PEU2	0.773	1.835				
PEU3	0.809	2.077				
PEU4	0.822	2.078				
PEU5	0.800	2.014				
PEU6	0.798	2.020				

Construct/Item	Item Loading	VIF	Alpha	Rh-A	Rh-C	AVE
Attitude Towards Technology (ATT)						
ATT1	0.861	1.830	0.822	0.823	0.894	0.738
ATT2	0.840	1.747				
ATT3	0.875	2.035				
Subjective Norms (SN)						
SN1	0.882	2.072	0.832	0.833	0.899	0.749
SN2	0.854	1.847				
SN3	0.860	1.880				
Technology Adoption (TA)						
TA1	0.796	1.380	0.796	0.701	0.831	0.622
TA2	0.753	1.313				
TA3	0.814	1.380				

Source: Authors' calculations using PLS-SEM based on survey data.

To assess discriminant validity, the approach proposed by Fornell and Larcker (1981) was employed. This method involved contrasting correlations among latent variables with the square root of the average variance extracted (AVE). (refer., Table 2).

Table 2. Validity and reliability of the constructs

Construct	ATT	PEU	PU	SN	TA
ATT	**0.859**				
PEU	0.578	**0.799**			
PU	0.626	0.731	**0.729**		
SN	0.688	0.581	0.643	**0.865**	
TA	0.716	0.710	0.710	0.719	**0.788**

Note. **PU:** Perceived usefulness; **PEU:** Perceived ease of use; **ATT:** Attitude Towards Technology; **SN:** Subjective Norms; **TA:** Technology Adoption.

Source: Authors' calculations based on Fornell and Larcker's (1981) criteria.

A discriminant validity assessment was conducted using Fornell and Larcker's (1981) approach. The square root of the average variance extracted (AVE) is used to compare correlations between latent variables. The results are presented in Table 2.

4.2 Structural equation model

To assess the structural equation model, a robust and reliable measurement model was developed using the PLS-SEM approach, with pairwise deletion applied for missing data. Variance Inflation Factor (VIF) scores (see Table 1) were consistently below the threshold of 5, indicating no multicollinearity. Ideally, the VIF values should be below 3 for optimal model quality (Hair et al., 2020).

Model evaluation included R-square, Q-square, and path significance for each endogenous construct. The R-square values, ranging from 0 to 1, exceeded the accepted thresholds, demonstrating strong explanatory power. Predictive relevance was assessed using Q-square, where values greater than 0 confirmed the model's predictive capability (Dul, 2020).

Model fit was evaluated using the Standardised Root Mean Square Residual (SRMR), which measures the discrepancy between observed and predicted correlation matrices. In this study, the SRMR value was 0.069, indicating a good model fit. Although values below 0.06 are ideal, SRMR values up to 0.08 are considered acceptable in well-specified models (Hair et al., 2020).

4.3 Necessary condition analysis (NCA)

To determine the influence of the constructs on technology adoption (TA), a structural model was developed. As presented in Figure 3 and Table 3, the results indicate statistically significant relationships. Perceived usefulness (PU) had a positive effect on TA ($\beta = 0.170$, $t = 4.360$, $p < 0.001$), as did perceived ease of use (PEU), which showed a stronger effect ($\beta = 0.277$, $t = 7.489$, $p < 0.001$). Similarly, both attitude toward technology (ATT) and subjective norms (SN) significantly influenced TA, with coefficients of ($\beta = 0.268$, $t = 7.065$, $p < 0.001$) and ($\beta = 0.264$, $t = 7.052$, $p < 0.001$), respectively.

The model demonstrated satisfactory outcomes across key evaluation metrics, including reliability, construct validity, discriminant validity, and collinearity, confirming its robustness and suitability for explaining students' acceptance of AI in accounting education.

Table 3. Direct relationship testing

Construct	Path coefficient	Standard deviation	T statistics (bootstrap)	P values	Confidence intervals	
					LOWER	**UPPER**
ATT -> TA	0.268	0.038	7.065	0.000	0.203	0.329
PEU -> TA	0.277	0.037	7.489	0.000	0.217	0.338
PU -> TA	0.170	0.039	4.360	0.000	0.109	0.237
SN -> TA	0.264	0.037	7.052	0.000	0.201	0.324

Note. **PU:** Perceived usefulness; P**EU:** Perceived ease of use; **ATT:** Attitude Towards Technology; **SN:** Subjective Norms; **TA:** Technology Adoption.

Source: Authors' computations using PLS-SEM with bootstrapping method (Hair et al., 2020).

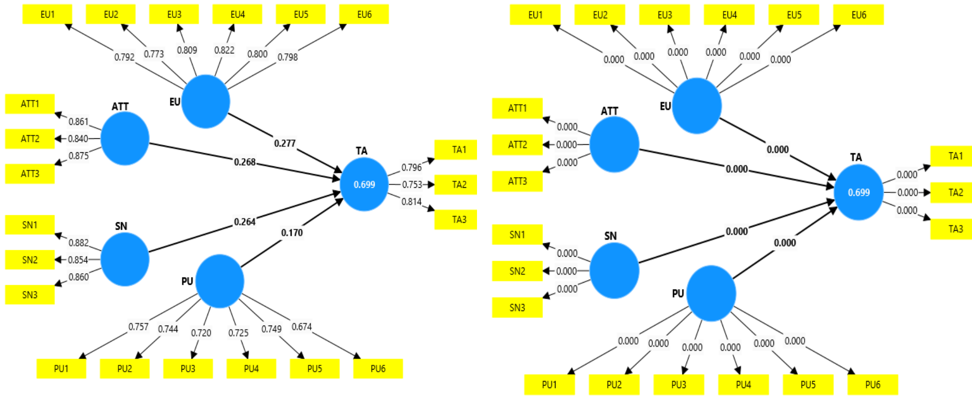

Figure 2. Structural equation model estimated

Source: Authors' output from PLS-SEM analysis using SmartPLS software.

To evaluate the necessity of each relationship, the effect size (d) of the necessary condition was calculated by dividing the ceiling area (i.e., the empty space) by the total scope area, representing the full range of possible observations (see Figure 3). According to Dul (2020), effect sizes are classified as small ($d \geq 0.10$), medium ($0.10 < d \leq 0.30$), and large ($d > 0.30$).

To test the statistical significance of the NCA effect sizes, a permutation test was applied, as recommended by Dul (2020). This method reduces the impact of spurious empty space created by unrelated variables or offsetting biases. The resulting p-values are interpreted using conventional significance levels (e.g., $\alpha = 0.05$). For a condition to be deemed theoretically or practically necessary, Dul (2020) suggests a minimum effect size of $d > 0.10$.

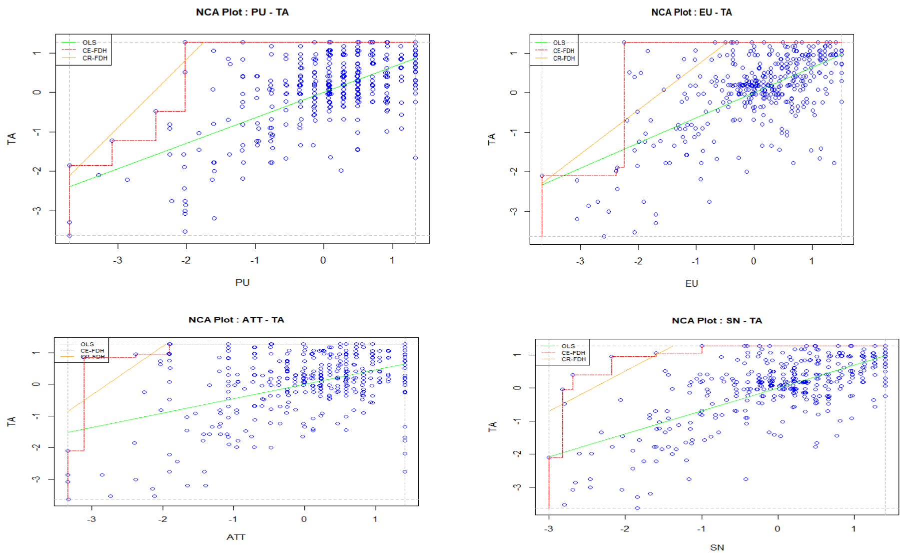

Figure 3. Dispersion and lines of necessary conditions

Source: Authors' calculations using NCA package in R, based on survey data.

Dul (2020) recommends a sample size of 10,000 permutations when testing effect sizes (d) for latent variables. Effect sizes are interpreted as follows: $d < 0.1$ indicates a small effect; $0.1 \leq d < 0.3$, a medium effect; $0.3 \leq d < 0.5$, a large effect; and $d \geq 0.5$, a very large effect.

In this study, Necessary Condition Analysis (NCA) was applied to the latent variable scores using 10,000 permutations (see Table 4), following Dul's guidelines. The CR-FDH ceiling technique was employed, as the variables are continuous. Results indicate that the tested dimensions represent both significant ($p = 0.05$) and meaningful ($d = 0.1$) necessary conditions for technology adoption (TA).

Table 4. Effect sizes of necessary conditions and significance test

Necessary condition effect sizes and significance tests				
	PU	**PEU**	**ATT**	**SN**
# observations	156	156		
Scope	24.732	25.410	23.302	21.632
X min	-3.700	-3.663	-3.333	-2.998
X max	1.334	1.509	1.410	1.405
Y min (TA)	-3.637	-3.637	-3.637	-3.637
Y max (TA)	1.276	25.410	1.276	1.276
	CR-FDH	**CR-FDH**	**CR-FDH**	**CR-FDH**
Ceiling zone	3.307	5.696	1.473	1.603
Effect size (d)	0.134	0.224	0.063	0.074
# above	3	15	2	4
c-accuracy	99.3%	96.3%	99.5%	99.0%
p-value	0.000	0.000	0.000	0.003
p-accuracy	0.000	0.000	0.000	0.001

Notes: CR-FDH = Ceiling Regression – Free Disposal Hull. We consider the general reference of the need effect size (d): $0 < d < 0.1$ 'small effect'; $0.1 \geq d < 0.3$ 'medium effect'; $0.3 \geq d < 0.5$ 'large effect', and $d \geq 0.5$ 'very large effect'. The indicated p values were estimated with 10,000 permutations.

Source: Authors' calculations based on Necessary Condition Analysis (Dul, 2020), using R software with 10,000 permutations.

As shown in Table 5, attitude toward technology (ATT) and subjective norms (SN) are not necessary conditions at lower levels of AI acceptance but become essential at higher acceptance thresholds. Specifically, both constructs only emerge as necessary once the acceptance rate surpasses 40%. This suggests that, while ATT and SN do not influence early adopters, they play a critical role in achieving higher levels of adoption.

Furthermore, although both perceived usefulness (PU) and perceived ease of use (PEU) are important, students appear to prioritise ease of use over perceived utility. The increasing values of PU and PEU in the percentiles indicate a growing awareness among students of these factors in the context of technology integration. This highlights the evolving importance of usability and perceived benefit in shaping adoption behaviour.

Table 5. Bottleneck CR-FDH percentile

Bottleneck	PU	PEU	ATT	SN
0	NN	NN	NN	NN
10	NN	NN	NN	NN
20	NN	NN	NN	NN
30	NN	2.3	NN	NN
40	5.0	10.8	NN	NN
50	10.7	19.3	NN	NN
60	16.3	27.7	2.3	0.2
70	21.9	36.2	9.0	9.4
80	27.5	44.7	15.7	18.5
90	33.2	53.2	22.4	27.7
100	38.8	61.6	29.1	36.8

Note. **PU:** Perceived usefulness; **PEU:** Perceived ease of use; **ATT:** Attitude Towards Technology; **SN:** Subjective Norms; **TA:** Technology Adoption.

Source: Authors' analysis using CR-FDH ceiling technique in NCA framework.

Moreover, ATT and SN values rise markedly from the 60th percentile onwards, indicating that social influence becomes increasingly important at higher levels of technology acceptance. This underscores the role of subjective norms in shaping students' attitudes toward technology. When developing strategies for integrating technology into accounting education, it is essential to consider both students' perceptions and the influence of their social environment. These insights can support educators and policymakers in enhancing student engagement and promoting effective adoption of technological innovations.

5. Discussion and conclusions

Accounting students' attitudes towards artificial intelligence (AI) significantly influence both their learning experiences and future professional practices. Those with positive attitudes are more likely to integrate AI into their accounting work. Perceived usefulness (PU) and perceived ease of use (PEU) are key drivers of this adoption, as validated by both the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) . This analysis offers nuanced insights into how these constructs interact to shape students' behavioural intentions.

The PLS-NCA results emphasise that enhancing PU, PEU, attitude towards technology (ATT), and subjective norms (SN) is critical to fostering AI adoption. Specific thresholds were identified as necessary for meaningful influence: 38.8% for PU, 61.6% for PEU, 29.1% for ATT, and 36.8% for SN. These findings highlight the importance of meeting certain minimum levels in each construct to effectively support adoption.

To positively influence learning outcomes, students must perceive AI as both beneficial and user-friendly. This requires an engaging and supportive educational environment in which students can interact with AI technologies in a practical and accessible way. As students become more familiar with AI applications in accounting, their confidence and willingness to adopt these tools are likely to increase.

Furthermore, as AI technologies continue to demonstrate practical value, their integration into accounting curricula will become increasingly indispensable. This shift will help reposition AI from a perceived challenge to a strategic enabler. Therefore, accounting education must focus on illustrating the relevance and benefits of AI, cultivating a learning culture that empowers students to effectively leverage technology in their future careers.

5.1 Implications

This study provides a theoretical framework that enables educational institutions and policymakers to better understand how accounting students perceive and adopt artificial intelligence (AI). By examining students' attitudes and behavioural intentions, the findings offer valuable insights to support the effective integration of AI into accounting curricula, thereby equipping graduates for the profession's ongoing digital transformation.

In the context of management accounting research, Partial Least Squares Structural Equation Modelling (PLS-SEM) is commonly employed to explore sufficient conditions, whereas Necessary Condition Analysis (NCA) remains underutilised despite its strength in identifying essential, non-substitutable factors. By combining both methods, this study adopts a dual analytical approach that captures both general relationships and critical thresholds, offering a more comprehensive understanding of the drivers of AI adoption. This methodological integration not only enriches theoretical perspectives, but also delivers actionable recommendations for AI implementation in educational and organisational contexts.

To prepare students for an AI-enhanced accounting profession, institutions must cultivate positive attitudes toward AI, address common concerns, and clearly demonstrate its practical value. Curricula should be updated to include core AI concepts, practical applications, and experiential learning opportunities that align with evolving industry demands.

Enhancing perceptions of AI's usefulness and ease of use is fundamental. The adoption of intuitive, user-friendly tools can reduce resistance and support student engagement. Moreover, collaboration with industry—through internships, guest lectures, and case-based learning—can help bridge the gap between academic knowledge and real-world practice, offering students both practical insight and valuable professional connections.

5.2 Limitations and further research

The conclusions of this study are established on a student sample, which may restrict the generalisability of the results to broader educational or professional settings. Although the sample is relatively large and drawn from multiple universities, the use of voluntary and convenience sampling may introduce self-selection bias, particularly among students with a higher interest in technology. Future studies should embrace probabilistic sampling or include participants from additional organisations to enhance representativeness.

Similarly, the focus on students limits the measurement of the investigation. analysing teachers' willingness and technological ability would provide a more comprehensive understanding of AI adoption in the accounting field, as faculty employment is critical for sufficient curriculum integration. Developing future research that includes both students and teachers could enhance the relevance and influence of insights into AI integration.

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