The Role of Technology Readiness in Shaping AI Adoption in Accounting Education: Evidence from Autonomous Colleges

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Abstract: The present study examined how students from independent institutions perceive the integration of artificial intelligence (AI) into accounting education, considering their readiness to adopt emerging technologies. The Technological Acceptance Model (TAM) was employed to investigate how the perceived ease of use (PEOU) of students influenced the relationship between their technological readiness (TR) and their willingness to adopt AI. Primary data was collected from 500 students through a structured questionnaire. The dimensions of technology readiness studied were innovativeness, optimism, insecurity, and discomfort. In addition, perceived utility (PU), perceived ease of use (PEOU), and technology adoption (TA) were also included as per the model. The data collected were subjected to reliability tests, correlational analysis, exploratory factor analysis, and mediation analysis. The results were reliable, with Cronbach's alpha values ranging from 0.802 to 0.984. The study's findings revealed that students' optimism and creativity regarding AI were evident, despite persistent feelings of apprehension and unease. When the correlational analysis showed a significant positive association among TR, PU, PEOU, and TA, in regression analysis, TR emerged as a strong predictor of TA. The results of the mediation analysis revealed that perceived ease of use plays a partial mediating role in the association between technological readiness and technology adoption, highlighting both direct and indirect effects. Further findings emphasise the importance of equipping students and addressing usability issues to facilitate the effective integration of AI in accounting education. Enhancing students' technical readiness and providing accessible AI tools enables educators and curriculum developers to prepare better future accountants who are predominantly dependent on technology.

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These insights offer crucial support for higher education stakeholders seeking to integrate technological innovation with its practical application in academic settings.

Keywords: Technology Readiness, Artificial Intelligence Adoption, Perceived Ease of Use, Technology Acceptance Model, Accounting Education

Introduction

In 2015, the World Economic Forum predicted that artificial intelligence (AI) would have a significant impact on the practices of accounting and auditing. By 2025, they anticipate that AI will handle approximately 30% of audits. A 2015 study examined 816 business leaders to determine how technology would soon impact the way businesses operate. The results showed what many people already suspected: that innovative technology would soon become an integral part of how businesses operate. A study from the McKinsey Global Institute also warns that AI will likely alter the way businesses perform their primary tasks, compelling them to reassess their processes and the skills they require.

However, despite these technological shifts and their growing prevalence in business, the accounting profession remains in a state of transition, as the integration of AI into professional practice continues to be influenced by environmental, cultural, and institutional factors (Bizarro & Dorian, 2017). AI systems are designed to compete with human-like learning, reasoning, and decision-making abilities (Soulpage, 2020). They are capable of automating tasks, detecting patterns in vast datasets, and generating actionable insights with accuracy and speed unmatched by traditional systems. Compared to conventional information systems, which primarily gather, store, process, and present data to aid decision-making, AI is regarded as more adaptive, intelligent, and efficient. Applications of AI in information technology include automated back-end processing, error-free reporting, enhanced security, and significant time and cost savings. Hence, it can be said that AI enables higher levels of automation and optimisation than earlier information systems. It helps create intelligent systems that not only process data but also learn, adapt, and operate in ways that mirror human cognition.

Nevertheless, the readiness of accounting graduates to operate effectively in this AI-driven environment remains a concern. Numerous studies highlight that accounting education has lagged behind technological advances in the industry (Jackling & De Lange, 2009; Tempone et al., 2012). While global corporations invest heavily in advanced technologies and integrate AI into their operations, academic curricula in accounting often fail to include courses that teach students about these developments. Research by Nen-Chen and Chang (2003), Stoner (2009), and Cory and Pruske (2012) suggests that employers expect graduates to possess strong IT skills, yet the curricula frequently do not reflect these expectations. Strong and Portz (2015) observed that while accounting students report relatively high competence in basic office automation tools, their skills in advanced technologies—such as AI, audit automation, and complex systems—are significantly weaker. Similarly, Stoner's (2009) longitudinal assessment of first-year accounting students over a decade showed limited progress in the adoption of advanced IT skills, with students showing greater comfort with internet and office applications than with databases, statistical software, or emerging technologies. The disparity between skills taught in academic programs and those demanded by companies is an indication of a persistent gap in accounting education.

Universities and colleges are expected to adapt curricula to improve graduates' employability and keep pace with technological progress (Tempone et al., 2012). Future accounting leaders will increasingly need to be proficient in AI and related technologies to remain competitive in the workforce. This fact makes it even more crucial to equip students with the necessary information, skill sets, and confidence to work in a business setting that utilises AI.

Beyond mere technical skills, a complex web of psychological and environmental factors influences how students respond to new technology. Fishbein and Ajzen (1975, 2010) pointed out a long time ago that our attitudes, perceptions, and beliefs have a significant impact on what we do—including whether or not we adopt technology. It is not just about what is practical or easy, either. Two fundamental mechanisms are proposed by Davis's Technology Acceptance Model (TAM, 1989), which are perceived utility (PU) and perceived ease of use (PEOU). When learners see that a tool may improve their performance and is user-friendly, their propensity to use it markedly rises. Subsequently, the Technology Readiness Index (TRI) was introduced by Parasuraman (2000), broadening the discourse. TRI examines the degree to which people feel comfort or anxiety around new technology, as well as their levels of creativity and optimism towards innovation in general. The readiness of pupils to use technology involves not just proficiency but also a combination of attitude, self-assurance, and inquisitiveness.

Although these models have been widely applied in various sectors, there is limited empirical evidence exploring how PU, PEOU, and TR interact to influence accounting students' adoption of AI, especially within the specific context of autonomous colleges in Kerala. These institutions occupy a distinctive position: they enjoy curricular flexibility and the potential to innovate, but students' readiness and perceptions regarding AI adoption remain largely underexplored. Existing research suggests that familiarity with generative AI tools influences students' attitudes and engagement in educational contexts (Simon et al., 2024; Suresh et al., 2024). In a similar vein, investigations within the field of professional accounting highlight an increasing acceptance of AI and a pressing need to equip students for its practical applications (Suresh, 2024). The intersection of financial technology advancements and sustainable digital methodologies underscores the need to equip students with essential technological skills (Dhanabhakyam & Suresh, 2024). This study examines the impact of Perceived Usefulness (PU) and PEOU on technology preparedness and AI adoption among accounting students, thereby contributing to the existing literature gap. In addition, the study examines the impact on students' technical preparation and AI-based solution adoption based on their evaluations of AI utility and usability.

Addressing this topic is essential for assessing students' technical preparedness, their confidence and motivation to embrace AI to help them in their academic and future professional endeavours. The skills required by future professionals are evolving in response to the rapid integration of AI into the fields of accounting and auditing. As a result, research is being conducted worldwide to address the use of AI in professional accounting. However, as far as the researcher's knowledge goes, very little is known about the perception and preparedness of accounting students who are the future accounting professionals, preparing for this technological transition. Therefore, this research sheds light on how prepared students are to utilise AI technologies in their future employment by concentrating on perceived usefulness, simplicity of use, and technical preparedness. The subject is current and pertinent, as it contributes to the changing scholarly literature and implications for professional training and curriculum development in India. This research examines accounting students in independent colleges in Kerala, where institutional autonomy permits curriculum innovation.

However, to the best of the researcher's knowledge, the significance and factors prompting AI adoption in education remain poorly understood. A lack of attention to the attitudes and readiness of Indian accounting students, particularly those in Kerala, regarding the integration of AI into their future careers, remains prevalent. Additionally, preceding research has focused on perceptions and knowledge rather than an integrated investigation of the working mechanism between technological readiness and AI adoption, including the mediating role played by students' perceived ease of use and perceived utility. This is indicative of the unpreparedness shown by accounting students pursuing degrees in private institutions in Kerala to incorporate AI in their academics and future careers. Bridging this gap is crucial to ensure that accounting education remains relevant and sufficiently equips future graduates for a profession that is increasingly shaped by artificial intelligence. By utilising the Technology Acceptance Model (TAM) and the Technology Readiness Index (TRI), this study aims to examine both psychological factors and students' readiness to adopt AI. The study results would help in the development of equitable and progressive curricula, teaching methods, and interventions that aim to improve student preparedness for future employment opportunities. Additionally, it would be beneficial to link students' academic knowledge with industry needs by exploring aspects that support or oppose AI adoption, including factors such as fear, uncertainty, enthusiasm, and innovation. The findings indicate that both societal and organisational influences collaboratively impact the integration of AI-driven technologies in accounting, enabling the usage of innovative practices within businesses and educational institutions. This study promotes the seamless integration of new technologies essential for accounting education, thereby equipping future accountants with the necessary skill sets for a landscape where artificial intelligence and machine learning are becoming increasingly pivotal.

2. Literature Review

This study is grounded on two fundamental theories: Rogers' Diffusion of Innovations Theory (DIT) and Fishbein and Ajzen's Reasoned Action Theory (RAT). Although they take significantly different approaches to the subject, both frameworks provide insights into how and why technical breakthroughs become popular. DIT focuses on how technology spreads across organizations, while RAT delves into how individuals make decisions about adopting new technology. Sometimes these viewpoints do not align precisely—especially within educational settings. Notably, as corporations and accounting firms bring AI into their workflows, the employment landscape for accounting graduates is shifting. In some cases, AI is creating fresh opportunities; in others, it is changing what those opportunities look like.

A multitude of college students depend on accounting software to augment their technical, auditing, and knowledge competencies. An essential element of accounting courses is preparing students for technological innovation. Students aspiring to future employment must possess the technical competencies that schooling may provide. A knowledge disparity exists between employers and students stemming from the differing rates at which educational institutions and industry stakeholders embrace developing technology. The research was very relevant to the ideas of diffusion and reasoned action. Recent studies further underscore the evolving role of AI in accounting education and practice. For instance, Suresh (2024) highlights that accountants increasingly recognise AI’s transformative potential in enhancing efficiency and accuracy within the field of accounting. Similarly, Suresh, Simon, and Nithyananda (2024) observed that undergraduate students in higher education institutions in Oman perceive generative AI tools as valuable in improving academic performance and digital readiness, suggesting the growing relevance of AI competence in the educational sector. Extending this perspective to professional practice, Suresh, Suresh, and Nithyananda (2025) emphasise that small audit firms, particularly in regions like Kerala, have significant untapped potential for leveraging AI technologies to strengthen audit quality and competitiveness.

2.2 Artificial Intelligence in Accounting and Auditing

Kokina and Davenport (2017) indicated a rapid transformation in the accounting and auditing professions. World-famous Big Four accounting companies have already invested in technology. Teams developed new technologies and innovative ways to utilise them. IBM Watson AI and KPMG developed AI audit tools. KPMG utilises McLaren Applied Technologies' predictive analytics to assess the risk associated with a financial statement. Halo is an analytics platform from PwC that connects AI and AR applications. PwC uses "Halo" instead of human-assisted business intelligence to look at accounting journals. In audits, EY uses big data and analytics to analyse and integrate vast amounts of client data (Issa et al., 2016). Deloitte produced Optix for AI and Auvenir to help small businesses with their audits. Deloitte and Kira Systems worked together to record, analyse, and extract keywords from rental agreements, employment contracts, declarations, and other documents. People assist the machine in developing new skills and finding helpful information (Whitehouse, 2016).

Accounting firms typically hire new graduates for entry-level positions that involve repetitive administrative tasks. EY predicted that the rise of AI would lead to a 50% drop in the annual recruiting pool, drastically altering the sector's college recruitment and employment landscape (Kokina & Davenport, 2017). Accounting tasks are well-suited for automation by AI and can also enhance precision, providing valuable insights for informed decision-making (Govil, 2020). Moreover, accountants are expected to conduct data analysis, rather than merely adhering to routine responsibilities. AI's ability to automate various activities, conduct ongoing audits, and provide real-time insights will have a significant impact on accounting. AI will increase accountants' productivity and innovation. AI should be promoted to them to help accounting students perform better. Employers are more interested in hiring accounting majors with excellent IT backgrounds. Accounting teachers should discuss their students' attitudes towards AI acceptance. In the upcoming decades, technology is expected to complement the accounting field. As machine intelligence develops, people must set themselves apart by "stepping up," "stepping aside," and "stepping in" to close the gap between humans and robots, according to Davenport and Kirby (2016) and Tufekci (2016).

2.3 Factors Influencing Individual Adoption of Technology.

The study investigated how attitudes influence the relationship between the technical training of accounting students and their utilisation of AI. Graduates of higher education must commit themselves to ongoing learning and career development. Numerous studies have already emphasised the need to equip students with various skills to meet the demands of the corporate sector. Educational institutions need to focus on this, as university accounting students often fall short in crucial competencies for professional practice. The study revealed a significant gap in the technological skills of accounting students. This study primarily focuses on identifying the factors that influence students' preparedness and readiness in adopting artificial intelligence. This study aimed to explore how accounting students utilise technology. The study investigated how attitudes influence the relationship between the technical training provided to accounting students and their utilisation of AI.

2.4 Technology Readiness

Technology readiness (TR) refers to the degree to which people are equipped to adopt and utilise new technologies for personal or professional purposes (Parasuraman, 2000). Parasuraman’s (2000) Technology Readiness Index (TRI) provides a comprehensive framework for assessing readiness by examining cognitive states that either promote or hinder adoption. This model emphasises that psychological predispositions are essential in technology acceptance, transcending concerns of access or availability. Lai (2008) posits that individuals' perceptions of technology encompass both positive and negative aspects, which together affect their readiness to adopt new tools and systems. Positive perceptions facilitate adoption, while scepticism or negative sentiments can generate resistance that hinders utilisation. (Parasuraman & Colby, 2015) identify four essential dimensions of technology readiness: innovativeness, discomfort, optimism, and insecurity. Optimism denotes the conviction that technology enhances efficiency, control, and flexibility in life. In contrast, innovativeness signifies the tendency to adopt new technologies early, which both contributes to and is influenced by the adoption process. Discomfort signifies feelings of powerlessness or being overwhelmed by technology, whereas insecurity indicates doubts regarding its reliability or functionality, thus serving as a barrier to its use. In addition to providing valuable insights into the factors influencing the use of cutting-edge technologies, such as artificial intelligence, in professional domains like accounting and auditing, this framework encompasses several dimensions that facilitate the assessment of technology adoption behaviour.

2.5 Adoption of Technology

Davis (1986) developed the Technological Acceptance Model (TAM) to provide a basic framework for studying the variables that influence individuals' decisions to accept or reject technological systems. The Technology Acceptance Model (TAM), derived from Fishbein and Ajzen's Theory of Reasoned Action (TRA) (1975), emphasises the influence of ideas, attitudes, and the ease of use and potential benefits of AI—mediate their readiness for new technologies and their academic use determinants of technology adoption: perceived usefulness (PU), which is the degree to which individuals believe that technology improves productivity or efficiency, and perceived ease of use (PEOU), which pertains to the simplicity and intuitiveness of utilising the technology. Research consistently demonstrates that perceived ease of use (PEOU) positively affects perceived utility (PU), as technology perceived as user-friendly is also considered more advantageous (Davis, 1989; Ma & Liu, 2004). Meta-analyses provide further evidence that perceived utility (PU) and perceived ease of use (PEOU) are crucial factors influencing technology adoption in various contexts (King & He, 2006). The Technology Acceptance Model (TAM) has been well validated in educational contexts. Simon et al. (2024) demonstrated that students' adoption of generative AI is more significantly influenced by their level of expertise than by their gender. This finding highlights the importance of incorporating AI-related content into the curriculum to equip students for future academic and professional challenges. Research indicates that the integration of technology in education is influenced by both individual and contextual factors, including institutional support and personal readiness (Venkatesh et al., 2003; Sumak et al., 2011).

In conjunction with the "Technology Acceptance Model", Parasuraman's (2000) Technology Readiness Index (TRI) elucidates the psychological factors influencing adoption behaviour, classifying them into four dimensions: optimism and innovativeness as facilitators, and discomfort and insecurity as barriers (Parasuraman & Colby, 2015; Lin & Hsieh, 2007). Individuals who are optimistic and innovative are more inclined to adopt AI, whereas skepticism and discomfort may impede its acceptance. Previous research indicates that students possessing higher technical competence exhibit an enhanced capacity to incorporate AI into their learning practices (Walczuch et al., 2007). In developing countries like India, barriers such as limited technological infrastructure, inadequate institutional support, and low self-confidence persistently hinder the adoption of digital technologies (Chatterjee et al., 2020; Suresh et al., 2024). These challenges increase uncertainty and anxiety, thereby diminishing both readiness and willingness to adopt emerging technologies.

Most published material emphasises Western contexts with developed technical infrastructure, despite the extensive validation of TAM and TRI across diverse global settings (Pan & Seow, 2016; PwC Global, 2022). Conversely, there exists a scarcity of empirical evidence regarding the interactions of PU, PEOU, TR, and Technology Adoption (TA) among accounting students in Kerala, India. Previous studies conducted in India primarily emphasize the integration of technology into general education, rather than delving into specialized fields such as accounting (Chatterjee et al., 2020). This study examines the extent to which PU, PEOU, and TR influence the utilization of AI among accounting students in autonomous institutions in Kerala, aiming to address the existing gap in understanding. The adaptability of these universities' curricula positions them well to foster innovation; however, they often do not receive the recognition they deserve within academic circles. This study not only enhances theoretical understanding of TAM and TRI but also offers actionable recommendations for better integrating AI into accounting programs. It situates the analysis within the Indian educational context and compares the findings with global trends. Creating interventions and programs that enhance technical skills, reduce barriers, and promote positive attitudes toward AI integration requires a deep understanding of these dynamics.

3. Research Questions of the Study

Recent studies reveal a connection between the implementation of AI technologies in accounting and auditing and the factors influencing students' readiness and willingness to incorporate these tools into their future careers. The performance of newcomers in these sectors will largely hinge on their technological proficiency and their ability to utilise AI solutions effectively. Data suggests a significant relationship between the willingness to accept AI and the readiness to implement it. The objective of this study was to investigate the relationship between technological preparedness and acceptance, as well as to examine the roles of perceived utility and perceived ease of use in this context. The study topics were clearly defined in connection with these essential issues.

RQ1. What level of preparation, utility, and ease of use do accounting students think their technology offers?

RQ2: How do accounting students feel about AI's applicability, user-friendliness, and technological acceptability in accounting and auditing?

RQ3: How do user attitudes affect the connection between technological readiness and AI adoption of accounting students?

This research examines the application of AI in accounting instruction for students at autonomous colleges in Kerala. The primary goal is to examine accounting students' technical preparedness and get their views on the usefulness and accessibility of AI tools.

The research examines the usefulness and student acceptability of AI in the fields of accounting and auditing. The research also examines whether students' perceptions—particularly their opinions on the ease of use and potential benefits of AI—mediate their readiness for new technologies and their academic use of AI. These goals aim to provide a comprehensive understanding of the variables that influence the adoption and integration of AI in accounting education within Kerala's autonomous institutions.

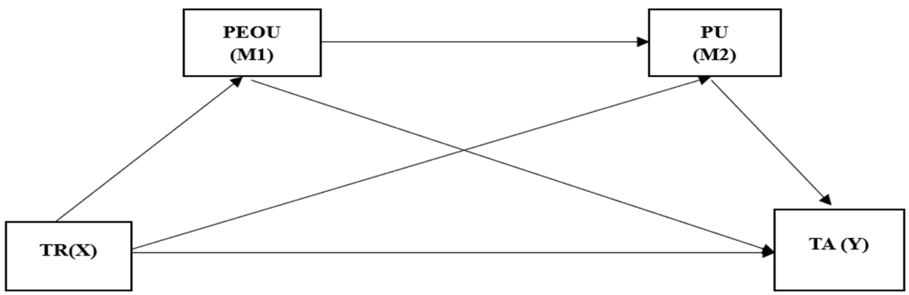

Fig.1. Conceptual Model framed by the authors referring to the TAM Model

The null and alternative hypotheses that address the study issues are as follows:

H0: Among accounting students, use perceptions (PEOU and PU) do not act as a mediator in the relationship between technological readiness (TR) and AI technology adoption (TA).

Ha: The relationship between technology readiness (TR) and the adoption of artificial intelligence (AI) by accounting students is moderated by perceptions (PEOU and PU).

4. Methodology

4.1 Research design

Quantitative correlational research was used in this work. The primary objective was to determine whether TR influences accounting students' adoption of AI and whether user perceptions, specifically PEOU and PU, alter this relationship. To compare variables or scores, correlational research uses statistical investigations (Creswell, 2014). The purpose of this study was to test hypotheses about the nature and strength of these connections.

4.2 Collection of Data

Kerala's autonomous colleges, particularly those in the Ernakulam region, were selected as the focus of the study because they represent some of the state's most academically sophisticated institutions and offer more freedom to modify curricula to meet changing industry demands. Kerala's high literacy rate and emphasis on higher education make it an ideal place to assess students' readiness to utilise AI in accounting. As an educational centre with an emphasis on prestigious independent institutions, the Ernakulam district offers access to a diverse and broad student body. For professionals, educators, and policymakers seeking to align accounting education with evolving technology, the study's relevance and validity are enhanced by the context selection.

The institutions were selected based on the following criteria: (a) they are reputable and accredited by the University Grants Commission, (b) they provide degree-oriented undergraduate accounting programs, and (c) they produce graduates for the Indian accounting and auditing professions. A weakness of the study is the non-random selection of the participating universities. The institutions were selected based on their geographical proximity to the researcher's study location and their alignment with the established criteria. Supplementary sites were included in the sample size to enable population-level generalisations. As the sample size increases, the standard error diminishes. The analysis of diverse institutions indicated an improvement in participant anonymity, a feature that might benefit universities investigating AI TA for accounting students. Even with a single location chosen, the standard error may remain minimal if the researcher attains the requisite sample size for a correlation analysis. The incorporation of pertinent topics in conventional accounting curricula at several universities indicates that the findings may be significant. After obtaining 500 replies, the researcher decided to remove the survey link. As a result, 500 replies (n = 100) were retained for data analysis. Consequently, a sample size of 500 was considered sufficient for analysis. Approximately one thousand replies were documented.

4.3 Sample Size

To assess whether a sample size of 500 respondents was sufficient for mediation analysis, the researcher used G*Power (Faul et al., 2009). This application is widely recognised for determining appropriate sample sizes in studies involving regression, mediation, and correlation analyses. With 500 participants, the sample size exceeded the minimum recommended threshold, ensuring robust statistical validity for regression and mediation analyses. Having a larger sample like this does affect the accuracy and reliability of your findings—especially since mediation analysis is an extension of multivariate regression. In the context of the Technology Acceptance Model (TAM), using a suitably large sample size enhances the generalizability and reliability of the results. A large sample size increases the level of trust that can be placed in the validity of the research findings, especially when analysing the connections between Technology Readiness (TR), Perceived Ease of Use (PEOU), and the adoption of artificial intelligence. As a consequence, the statistical results obtained from this research may be considered reliable and trustworthy, thereby reducing the likelihood of bias or random error occurring.

4.4 Instrumentation

The investigation utilised established and widely acknowledged tools to guarantee methodological rigour and validity. In particular, two survey frameworks were utilised: the Technology Readiness Index (TRI 2.0) and the Technology Acceptance Model (TAM). The TRI 2.0, developed by Parasuraman and Colby (2015), comprises 16 items that assess four dimensions of technology readiness: insecurity, discomfort, innovativeness, and optimism. Davis's (1989) TAM scale comprises 12 items, divided into six that evaluate Perceived Usefulness (PU) and six that evaluate Perceived Ease of Use (PEOU). Responses to TRI items were recorded using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). In contrast, TAM and technology adoption items were assessed on a 7-point scale, ranging from 1 (very implausible) to 7 (very likely). Participants evaluated their degree of agreement with each statement. This method facilitated dependable and uniform data gathering, rooted in established theoretical frameworks, thus enhancing the study's construct validity.

4.5 Validity and Reliability

The statistical analyses were performed utilising SPSS 20, a commonly used software tool in the field of social science inquiry. The approaches utilised comprised descriptive statistics, regression analysis, and confirmatory factor analysis (CFA). To assess the validity and reliability of the measurement instruments, exploratory factor analysis (EFA) and Cronbach's alpha were applied. Introduced by Cronbach in 1951, this coefficient assesses the internal consistency of survey scales, with values typically ranging from 0.70 to 0.95, which are considered acceptable in the field of social science (Tavakol & Dennick, 2011). The overall Cronbach's alpha in this study was 0.931, indicating a strong level of internal consistency across all scales. The Technology Readiness dimensions yielded values of 0.802 for discomfort, 0.850 for insecurity, 0.921 for optimism, and 0.913 for innovativeness. The coefficients for the Technology Acceptance Model (TAM) were recorded as follows: 0.984 for Perceived Usefulness, 0.923 for Perceived Ease of Use, and 0.959 for Technology Adoption. Given that all values exceeded the recommended threshold, the scales demonstrated remarkable reliability, thereby laying a solid groundwork for future statistical analyses and bolstering the trustworthiness and robustness of the study's findings.

4.6 Exploratory Factor Analysis Results

EFA was performed on responses from 500 participants to assess the validity and reliability of the measurement instruments. The primary objective was to examine whether the observed variables accurately represented the underlying dimensions of technology readiness and the integration of artificial intelligence in accounting. EFA was instrumental in revealing the latent structure of the constructs, thereby refining measurement items to ensure alignment with the intended variables and strengthening construct validity. Furthermore, the analysis enabled data reduction, consolidating a large set of variables into a smaller, more meaningful set while retaining essential information. This process provided a robust basis for subsequent statistical analyses and enhanced the overall methodological rigour of the study.

Table 1. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.756
Bartlett's Test of Sphericity	Approx. Chi-Square	656.509
	df	120
	Sig.	0

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.756, suggesting a moderate to good level of adequacy for performing factor analysis (values exceeding 0.70 are deemed acceptable). The results of Bartlett's Test of Sphericity indicated a Chi-Square value of 656.509 with 120 degrees of freedom, achieving statistical significance at $p < 0.001$. This confirms that the correlation matrix is not an identity matrix. The findings collectively suggested that the data were suitable for Exploratory Factor Analysis.

Table 2. Communalities

Communalities		
	Initial	**Extraction**
OP1	0.774	0.743
OP2	0.766	0.805
OP3	0.682	0.625
OP4	0.844	0.891

INNO1	0.693	0.556
INNO2	0.728	0.626
INNO3	0.763	0.837
INNO4	0.701	0.548
DISCO1	0.5	0.439
DISCO2	0.634	0.74
DISCO3	0.634	0.612
DISCO4	0.548	0.459
INSEC1	0.7	0.561
INSEC2	0.809	0.862
that 69.2% of the students were female and 30.8% were male	0.773	0.745
INSEC4	0.589	0.451
Extraction Method: Principal Axis Factoring.		

The communalities after extraction ranged from 0.439 to 0.891, indicating that the removed factors explained most of the variance in the items. Most of the values were higher than the suggested level of 0.50, which means that the variables were well represented in the factor solution. Some items, such as DISCO1 (0.439), DISCO4 (0.459), and INSEC4 (0.451), had slightly smaller communalities, but they were still close to the acceptable cut-off, so they were retained to maintain content validity.

Table 3. Total Variance Explained

Factor	Eigenvalue	% of Variance	Cumulative %
1	6.028	37.68	37.68
2	1.911	11.94	49.62
3	1.514	9.46	59.08
4	1.047	6.55	65.63

Extraction Method: Principal Axis Factoring; Rotation Method: Oblimin with Kaiser Normalization

Principal Axis Factoring was used for exploratory factor analysis. Four factors with eigenvalues greater than 1 were found. They described 65.63% of the overall variance after rotation. It was found that Factor 1 accounted for 37.68% of the variation, Factor 2 accounted for 11.94%, Factor 3 accounted for 9.46%, and Factor 4 explained 6.55% of the variation. This total variation is higher than the usual cutoff of 60% in social science studies, indicating that the factors pulled are a good representation of the underlying data structure.

Table 4: Pattern Matrix

Pattern Matrix				
	Factor			
	1	**2**	**3**	**4**
OP1	0.789	-0.041	-0.058	0.155
OP2	0.922	0.026	0.013	-0.048
OP3	0.672	-0.097	0.061	0.106
OP4	0.898	-0.07	0.088	-0.047
INNO1	0.113	-0.673	-0.008	0.07
INNO2	-0.101	-0.69	0.326	-0.056
INNO3	-0.003	-0.935	-0.162	0.089
INNO4	0.212	-0.632	-0.021	-0.013
DISCO1	0.111	0.055	0.603	0.083
DISCO2	-0.185	-0.122	0.829	0.099
DISCO3	0.104	0.137	0.701	0.174
DISCO4	0.163	-0.138	0.597	-0.166
INSEC1	0.045	-0.153	0.139	0.619
INSEC2	-0.038	0.011	0.047	0.928
INSEC3	0.098	-0.011	-0.121	0.853
INSEC4	0.07	-0.007	0.316	0.459

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalisation. a. Rotation converged in 9 iterations.

As expected from the theory behind Technology Readiness, the pattern grid showed a clear four-factor answer. Items OP1 through OP4 had high loadings on Factor 1, which is the Optimism dimension (loadings ranging from 0.672 to 0.922). Items INNO1 through INNO4 had significant loading on Factor 2 (ranging from -0.632 to -0.935), indicating the innovativeness dimension.

The items DISCO1 through DISCO4 scored highly on Factor 3 (0.597 to 0.829), which shows the Discomfort factor. Lastly, items INSEC1 through INSEC4 loaded mostly on Factor 4 (ranging from 0.459 to 0.928), indicating the Insecurity dimension. All of the items had loadings above the acceptable level of 0.50, except for INSEC4 (0.459), which was retained due to its theoretical importance and its role in covering the entire build. The factors' discriminant validity is also supported by the fact that there are no significant cross-loadings.

Table 5. Factor Correlation Matrix

Factor Correlation Matrix				
Factor	**1**	**2**	**3**	**4**
1	1	-0.442	0.291	0.388
2	-0.442	1	-0.291	-0.172
3	0.291	-0.291	1	0.331
4	0.388	-0.172	0.331	1
Extraction Method: Principal Axis Factoring.				
Rotation Method: Oblimin with Kaiser Normalisation.				

The factor correlation matrix shows modest relationships among retrieved components, with values ranging from -0.442 to 0.388. A negative correlation (−0.442) between

Factors 1 and 2 indicates weaker innovativeness, whereas a positive correlation (0.388) between Factors 1 and 4 shows increased insecurity. The variables' discriminant validity and lack of multicollinearity are confirmed by all correlations below 0.85. Oblimin rotation was suitable since the elements are connected yet separate.

5. Data Analysis Results

Table 6: Demographic Profile of the Respondents

Variable	Categories	Frequency	Percent
Gender	Male	154	30.80%
	Female	346	69.20%
Age	Below 20	157	31.40%
	20–24	327	65.40%
	25–29	16	3.20%
Academic Year	First Year	46	9.20%
	Second Year	118	23.60%
	Third Year	137	27.40%
	Post Graduation	199	39.80%
Institution	Nirmala	79	15.80%
	MA	177	35.40%
	SH	119	23.80%
	STC	82	16.40%
	STP	43	8.60%
Specialisation	Finance	104	20.80%
	Taxation	117	23.40%

The demographic profile revealed 69.2% of female students and 30.8% of male students. Most participants belonged to the 20–24-year age group (65.4%), followed by those under 20 years (31.4%), with a small proportion aged 25–29 years (3.2%). Regarding academic year, the largest group was postgraduates (39.8%), followed by third-year students (27.4%), second-year students (23.6%), and first-year students (9.2%). In terms of institutional affiliation, the highest representation was from MA

(35.4%), followed by SH (23.8%), Nirmala (15.8%), STC (16.4%), and STP (8.6%). With respect to specialisation, 23.4% of the respondents pursued taxation, while 20.8% specialised in finance.

Table 7: AI Awareness, Usage, and Proficiency Characteristics of Respondents

Comfort Level with AI	Very Comfortable	171	34.20%
	Comfortable	175	35.00%
	Neutral	122	24.40%
	Uncomfortable	24	4.80%
	Very Uncomfortable	8	1.60%
Frequency of Using AI	Daily	103	20.60%
	Weekly	61	12.20%
	Monthly	70	14.00%
	Rarely	210	42.00%
	Never	56	11.20%
Accounting Software Used	Excel	280	56.00%
	Tally	172	34.40%
	SAP	48	9.60%
Proficiency Level	Expert	16	3.20%
	Proficient	78	15.60%
	Intermediate	280	56.00%
	Beginner	86	17.20%
	No Experience	40	8.00%
Resources Availability	Strongly Agree	71	14.20%
	Agree	220	44.00%
	Neutral	170	34.00%
	Disagree	16	3.20%
	Strongly Disagree	23	4.60%
Awareness of AI	Yes	329	65.80%
	No	163	32.60%

	Can't Say	8	1.60%
Understanding of AI	Excellent	48	9.60%
	Good	156	31.20%
	Fair	137	27.40%
	Poor	63	12.60%
	No Understanding	96	19.20%
Areas of Contribution of AI	Data Analysis	148	29.60%
	Taxation	106	21.20%
	Auditing	105	21.00%
	Financial Reporting	63	12.60%
	Forecasting & Budgeting	47	9.40%
	Risk Management	24	4.80%
	None	7	1.40%
Frequency of Using AI in Academic Tasks	Daily	65	13.00%
	Weekly	86	17.20%
	Monthly	62	12.40%
	Rarely	166	33.20%
	Never	121	24.20%

The results indicate that a majority of respondents were either very comfortable (34.2%) or comfortable (35.0%) in using AI, while about one-fourth (24.4%) remained neutral, and a small fraction reported discomfort (6.4%). In terms of usage frequency, most respondents used AI infrequently (42.0%), with 20.6% using it daily and 12.2% using it weekly. Excel emerged as the most widely used accounting software (56%), followed by Tally (34.4%) and SAP (9.6%).

Regarding proficiency, over half of the respondents (56%) identified themselves as having an intermediate level, while only 3.2% reported being experts. Most respondents agreed (44%) or strongly agreed (14.2%) that resources for AI use were available, while a small proportion disagreed (7.8%). Awareness of AI was high, with 65.8% reporting familiarity.

In terms of understanding, the highest share rated themselves as having good (31.2%) or fair (27.4%) knowledge, while 19.2% reported no understanding. Respondents highlighted data analysis (29.6%), taxation (21.2%), and auditing (21.0%) as the main areas of AI contribution. However, academic use of AI was relatively modest, with only 13% reporting daily use, while most used it rarely (33.2%) or never (24.2%).

Table 8: Scores on the Constructs of the Process Mediation by Education Level.

Academic Year	TRMEAN	PUMEAN	PEOUMEAN	TAMEAN
First Year	3.1073	4.1413	4.3551	4.1522
Second Year	3.1769	4.5028	3.9873	3.9915
Third Year	2.917	4.2591	3.9124	3.8102
Post-Graduation	3.2183	4.3241	4.2278	4.1407
Total	3.1157	4.3317	4.0963	4.016

The mean score analysis indicates varying perceptions of technology readiness (TR), perceived usefulness (PU), perceived ease of use (PEOU), and technology adoption (TA) across academic levels. Postgraduate students reported the highest TR (3.22), suggesting greater confidence and readiness, while third-year students showed the lowest (2.92). PU was rated highest by second-year students (4.50), possibly reflecting increased academic exposure and recognition of AI's practical benefits, whereas first-year students rated it lowest (4.14). Interestingly, first-year students scored highest on both PEOU (4.36) and TA (4.15), indicating enthusiasm and openness to adopting new technologies at the entry level. In contrast, third-year students had the lowest scores in these areas (3.91 and 3.81, respectively), possibly due to the pressures of academic work or the critical evaluation of technology's limitations. Overall, the findings suggest that while technology adoption is generally favourable, perceptions differ by academic year, with first-year enthusiasm, second-year recognition of usefulness, and postgraduate confidence standing out as key patterns.

Table 9. Descriptive Statistics for the Dimensions of Technology Readiness

Construct	Item	Mean (μ)	Std. Deviation (σ)
Optimism	OP1	3.77	1.19
	OP2	3.48	1.08
	OP3	3.47	1.07
	OP4	3.49	1.15
	Overall Score	3.55	1.01
First Year		3.27	1.1
Second Year		3.92	0.81
Third Year		3.3	1.04
Post Graduation		3.58	1
Innovativeness	INNO1	2.72	1.03
	INNO2	2.55	1.09
	INNO3	2.85	1.09
	INNO4	3.04	1.1
	Overall Score	2.79	0.89
First Year		2.91	1.14
Second Year		2.93	1
Third Year		2.63	0.84
Post Grad		2.79	0.78
Discomfort	DISCO1	2.73	1.09
	DISCO2	2.91	1.08
	DISCO3	2.96	0.98
	DISCO4	2.94	1
	Overall Score	2.88	0.82

First Year		2.93	0.99
Second Year		2.63	0.82
Third Year		2.78	0.7
Post Grad		3.09	0.81
Insecurity	INSEC1	3.13	1.21
	INSEC2	3.29	1.17
	INSEC3	3.5	1.26
	INSEC4	3.02	1.23
	Overall Score	3.23	1.01
First Year		3.32	0.83
Second Year		3.22	0.93
Third Year		2.96	0.95
Post Grad		3.41	1.1

The descriptive statistics highlight distinct patterns across all dimensions of technology readiness among the 500 respondents. The overall mean score for optimism was the highest (3.55), indicating that people generally held a favourable view of technology's advantages. Second-year students showed the most remarkable optimism (3.92), while third-year students showed the least (3.30). Innovativeness showed the lowest overall mean (2.79), suggesting relatively moderate confidence in experimenting with or adopting new technologies, with slight variation across academic years. Discomfort averaged 2.88, indicating a moderate level of unease with technology, and was highest among postgraduates (3.09), suggesting some apprehension despite their higher academic level. Insecurity had a mean of 3.23, indicating a fair degree of uncertainty or lack of confidence in relying on technology, particularly among third-year students (mean = 2.96). Overall, the findings suggest that while students are broadly optimistic about technology, their willingness to innovate and their confidence in using technology remain tempered by concerns of discomfort and insecurity, which vary with academic seniority.

Table 10. Descriptive Statistics for the Beliefs of the Technology Acceptance Model.

Construct	Item	Mean (μ)	Std. Deviation (σ)
Perceived Usefulness (PU)	PU1	4.48	1.86
	PU2	4.4	1.9
	PU3	4.32	1.83
	PU4	4.14	1.86
	PU5	4.31	1.82
	PU6	4.33	1.9
	Overall Score	4.33	1.79
First Year		4.14	2.61
Second Year		4.5	1.6
Third Year		4.26	1.64
Post Graduation		4.32	1.77
Perceived Ease of Use (PEOU)	PEOU1	3.85	1.92
	PEOU2	4.09	1.82
	PEOU3	4	1.78
	PEOU4	4.1	1.94
	PEOU5	4.19	1.88
	PEOU6	4.35	1.83
	Overall Score	4.1	1.67
First Year		4.36	2.03
Second Year		3.99	1.52
Third Year		3.91	1.62
Post Graduation		4.23	1.69

The results of descriptive analysis of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) revealed mostly positive evaluations among the respondents. PU achieved a notable overall mean of 4.33, indicating that students generally acknowledge the advantages of AI in accounting. Second-year students reported the most significant perceived utility (4.50), while first-year students reported the lowest (4.14). PEOU demonstrated a robust overall mean of 4.10, indicating that students see AI apps as comparatively user-friendly. First-year students exhibited the highest ease-of-use rating (4.36), reflecting their initial enthusiasm and willingness to adopt AI technology. However, third-year students had the lowest ease of use score (3.91), suggesting that their coursework or assessments were more challenging for them. The postgraduates' Mean scores for perceived utility and perceived ease of use were 4.32 and 4.23, respectively, indicating their well-rounded views. The findings reveal that students at different academic levels see AI as helpful and approachable, based on their exposure and experiences.

Table 11. Descriptive Statistics for Behavioural Intentions Towards AI Technology Adoption in Accounting

Construct	Item	Mean (μ)	Std. Deviation (σ)
Technology Adoption (TA)	TA1	4.01	1.65
	TA2	4.03	1.63
	Overall Score	4.02	1.61
First Year		4.15	1.87
Second Year		3.99	1.47
Third Year		3.81	1.54
Post Graduation		4.14	1.66

According to a survey with a mean score of 4.02, students are inclined to employ AI technology in accounting. The most ambitious students were first-years (4.15), indicating that they were ready to apply AI at an early stage of their academic careers. Either as a result of academic pressure or a critical evaluation of the practical difficulties posed by technology, third-year students reported the lowest intention (3.81). Strong adoption intentions among postgraduates (4.14) suggest increased exposure and intellectual maturity. The findings indicate that students from diverse educational backgrounds are interested in behaving well in the presence of AI. Third-year students, however, performed worse, indicating specific problems that would need further research.

Table 12. Descriptive statistics for behavioural intentions towards AI technology adoption in accounting

Construct	Mean (μ)	Standard Deviation (σ)
Technology Adoption (TA)		
TA1	4.01	1.65
TA2	4.03	1.63
Overall score	4.02	1.61
First Year	4.15	1.87
Second Year	3.99	1.47
Third Year	3.81	1.54
Post Graduation	4.14	1.66

The descriptive statistics indicate that overall, students reported a moderate to high level of behavioural intention towards the adoption of AI in accounting and auditing, with an average score of 4.02. Among the academic groups, students of first-year (M = 4.15, SD = 1.87) and students of post-graduation (M = 4.14, SD = 1.66) demonstrated the highest mean scores, suggesting stronger intentions to adopt AI technologies compared to second-year students (M = 3.99, SD = 1.47) and third-year students (M = 3.81, SD = 1.54). The relatively close mean values across groups indicate a consistent overall perception. However, the slightly lower scores among third-year students suggest a dip in enthusiasm or confidence in AI adoption at that stage.

Table 13. Correlation Analysis

Variables	TR Optimism	TR Innovativeness	TR Discomfort	TR Insecurity	PU	PEOU	TA
PU	.528**	.294**	.363**	.529**	1	.817**	.614**
PEOU	.566**	.443**	.434**	.603**	.817**	1	.763**
TA	.475**	.340**	.513**	.487**	.614**	.763**	1

*Note: **p < 0.01 (2-tailed). TR dimensions include Optimism, Innovativeness, Discomfort, and Insecurity*

Table 8 revealed a significant positive correlation among the key constructs. PU and PEOU were highly correlated (r = .817, p < .01), indicating that students who found AI systems functional also expected them to be easy to use. Both PU (r = .614, p < .01) and PEOU (r = .763, p < .01) showed strong positive correlations with Technology Adoption (TA), suggesting that favourable perceptions directly enhance students' intentions to adopt AI. Optimism, discomfort, innovativeness, and insecurity, which are dimensions of Technology Readiness, demonstrated moderate positive correlations with PU, PEOU, and TA, with the highest observed between insecurity and PEOU (r = .603, p < .01). None of the correlations exceeded the 0.90 threshold, indicating the absence of multicollinearity concerns. These results provide preliminary support for the hypothesised relationships and justify further testing through regression and mediation analyses.

5.1 Hypothesis Testing and Mediation Analysis

The current study examined the function of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as mediators on the association between Technology Readiness (TR) (independent variable) and Technology Adoption (TA) (dependent variable). Mediation analysis was conducted using AMOS software using a structural equation modelling (SEM) methodology. AMOS was selected for its capacity to estimate multiple mediators within a single model simultaneously, its extensive path analysis capabilities, and its reporting of several goodness-of-fit indicators to assess the model's overall appropriateness. These attributes make AMOS particularly adept at analysing complex mediation models in behavioural and social science research. The outcomes of this analysis will be delineated and scrutinised in the subsequent section.

Path 1: Perceived Usefulness mediates the relationship between Technology Readiness and Technology Adoption

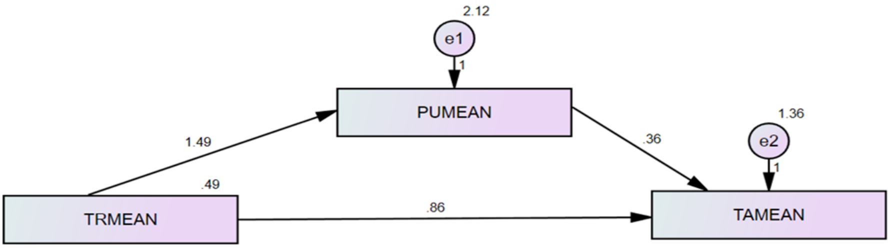

Fig 2: PU mediating TR and TA

TR had a significant effect on PU and TA as revealed by mediation analysis. The relationship from TR to PU was statistically significant ($\beta = 1.487$, $p < .001$), as was the direct relationship from TR to TA ($\beta = .864$, $p < .001$). Additionally, PU was a significant predictor of TA ($\beta = .355$, $p < .001$). The bootstrap analysis indicated a significant indirect effect of TR on TA via PU (95% CI = 0.390–0.671, p = 0.001), with a standardised effect ranging from 0.172 to 0.290. The results indicate partial mediation by PU on the association between TR and TA, suggesting that TR directly influences technology adoption while also exerting an indirect effect through students' perceptions and the usefulness of technology.

Path 2: Perceived Ease of Usefulness mediates the relationship between Technology Readiness and Technology Adoption

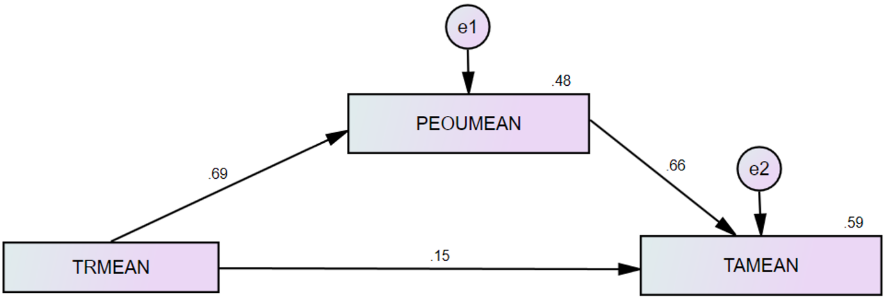

Fig 3: PEOU mediating TR and TA

The indirect impact of TR on TA via PEOU was computed as 1.043 (a*b), particularly (1.648 * 0.633), indicating a considerable mediating function of PEOU. The bias-corrected bootstrap confidence intervals for this effect (0.892 to 1.212) do not include zero, and the p-value is 0.001, indicating that the mediation effect is statistically significant. Higher technological readiness among students is expected to lead to their greater adoption of AI, primarily due to their perception of user-friendliness. The results indicate that Perceived PEOU partially mediates the relationship between TR and TA. TR has a direct significant influence on TA ($\beta = 0.348$, $p = .001$) with a considerable indirect influence on PEOU ($\beta = 1.043$, 95% CI = 0.892–1.212, $p = .001$). The importance of both direct and indirect pathways signifies that the mediation is partial, implying that TR influences TA both directly and indirectly via PEOU.

Table 14. Results of Bootstrap Analysis for Mediation Effects of PU and PEOU

Path	Direct Effect (β)	Indirect Effect (β)	95% CI Lower Bound	95% CI Upper Bound	Two-Tailed Significance (p)	Regression Estimate (β)

TR → PEOU → TA	0.348	1.043	0.892	1.212	0.001	TR → PEOU = 1.648 TR → TA = 0.348 PEOU → TA = 0.633
TR → PU → TA	0.864	0.528	0.39	0.671	0.001	TR → PU = 1.487 TR → TA = 0.864 PU → TA = 0.355

Table 8 illustrates a mediation effect of PEOU and PU on the relationship between TR and TA. For the TR–PEOU–TA path, the direct effect remained significant ($\beta = 0.348$, $p = 0.001$), with a strong indirect effect ($\beta = 1.043$) within the 95% bias-corrected confidence interval of 0.892 to 1.212, confirming partial mediation. Similarly, for the TR–PU–TA path, the direct influence was statistically significant ($\beta = 0.864$, $p = 0.001$), and the indirect effect ($\beta = 0.528$) to fell within the 95% confidence interval of 0.390 to 0.671, again indicating partial mediation. The regression estimates further confirm that TR has a substantial positive influence on both PEOU ($\beta = 1.648$, $p < 0.001$) and PU ($\beta = 1.487$, $p < 0.001$), which in turn significantly predict TA ($\beta = 0.633$ and $\beta = 0.355$, respectively). The mediation results were tested using a bootstrap procedure with 2,000 resamples to construct a 95% confidence interval, ensuring the robustness of the indirect effect estimates. Overall, the findings suggest that technology readiness not only directly enhances technology adoption but also puts forth an additional indirect influence through the perceptions of PEOU, thereby strengthening adoption behaviour among students.

6. Summary of Findings

With an emphasis on the mediating functions of perceived usefulness (PU) and perceived ease of use (PEOU), the current research investigated the connection between technology readiness (TR) and the adoption of AI in two professions, accounting and auditing. According to the descriptive data, accounting students typically expressed a medium to high level of readiness for utilising AI. Additionally, their opinion on the usefulness and usability of these technologies was found to be favourable. A bootstrap approach using 2,000 resamples at a 95% confidence interval revealed that PEOU and PU have a strong mediating effect on the association between TR and TA. The TR–PEOU–TA route showed a significant indirect impact ($\beta = 1.043$, CI: 0.892–1.212) and a significant direct effect ($\beta = 0.348$, $p = 0.001$), suggesting partial mediation. Partial mediation was also confirmed by the TR–PU–TA route, which showed a substantial direct impact ($\beta = 0.864$, $p = 0.001$) and a notable indirect effect ($\beta = 0.528$, CI: 0.390–0.671). All of these findings provide answers to the study questions. Accounting students believe they are sufficiently equipped to integrate technology (RQ1), believe AI is practical, easy to use, and appropriate for their field (RQ2), and demonstrate that user perceptions have a significant influence on the association between readiness and adoption of AI technology (RQ3). Therefore, the null hypothesis (H0) was rejected and the alternative hypothesis (Ha) was accepted.

6.1 Practical Implications

The results have significant ramifications for professional training and accounting education. Since it has been demonstrated that both PEOU and PU enhance the adoption of AI technologies, educational institutions must do more than provide students with access to AI-related resources; they also need to ensure that students perceive these tools as practical and easy to use. Integrating AI into accounting courses through case-based learning, simulations, and practical training workshops may enhance students' confidence and competence, thereby promoting higher adoption intentions.

To close the gap between professional practice and academic preparation, universities, professional associations, and auditing companies must collaborate. Students can leverage their technological preparedness into valuable skill sets through organised internship opportunities, industry expert guest lectures, and exposure to real-world AI auditing tools. As AI technologies continue to advance and reshape accounting and auditing procedures, it will also be critical to foster flexibility and ongoing learning.

6.2 Limitations and Future Research

Even when study results contribute to the existing body of knowledge, they are not immune to limitations. First, because the study only examined accounting students, it is possible that the results do not fully reflect the views of working auditors, who face more professional pressures and ethical issues. In the future, the studies should include accountants and practitioners from both the "Big Four" companies and mid-tier firms. However, utilising self-reported numerical metrics may lead to inaccuracies, such as overestimating societal approval or preparedness. Employing a mixed-methods approach that incorporates focus groups or interviews could yield more profound and more nuanced insights into individuals' perspectives on the adoption of AI. Third, the investigation focused solely on two parameters: PEOU and PU. Additional elements that were not addressed but could influence the implementation of AI encompass technological infrastructure, social challenges, legal frameworks, and organisational support. To achieve a more thorough understanding, subsequent investigations could gain from the inclusion of these environmental factors. The cross-sectional pattern reveals a specific instant in time. Longitudinal studies can track students' views and plans regarding the use of AI as they progress through their careers. This provides further evidence that AI can be effective in accounting in the long run.

6.3 Conclusion

The results of the study indicated technology readiness of accounting students—especially their optimism and innovativeness—alongside their assessments of technology's perceived usefulness and ease of use, significantly influenced the effective incorporation of Artificial Intelligence (AI) into accounting education. The mediation analysis highlighted that Perceived Ease of Use (PEOU) plays a noteworthy role in enhancing the connection between Technology Readiness and AI adoption, emphasising both direct and indirect pathways through which readiness promotes adoption. The findings propound the need for curriculum developers and higher educational institutions to establish targeted training initiatives, workshops, and technology-enhanced learning modules that not only enhance technical skills but also alleviate the unease and uncertainty associated with integrating new technologies. These initiatives can effectively influence students' views on the practicality and value of AI, leading to a more seamless integration and preparing graduates with the essential skills for thriving in technology-oriented accounting professions.

This study contributes to the expanding literature on the Technology Acceptance Model (TAM) by illustrating its relevance in understanding AI adoption in accounting education, particularly in the Indian context. Also, valuable insights are provided to educators, institutional leaders and policymakers who seek to integrate technological innovations into accounting education. Future investigations could expand on these findings by utilising longitudinal studies to monitor shifts in perceptions over time, performing cross-cultural comparisons, or incorporating additional constructs such as attitude, behavioural intention, and contextual dynamics. Investigating these dimensions will enhance our understanding of AI's enduring impact on accounting education provided to students and professional practice in the accounting and auditing professions.

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