Global Scientific and Academic Research Journal of Economics, Business and Management
ISSN: 2583-5645 (Online)
Frequency: Monthly
Published By GSAR Publishers
Journal Homepage Link- https://gsarpublishers.com/journals-gsarjebm-home/

ARTIFICIAL INTELLIGENCE ADOPTION AMONG ACCOUNTANTS IN THE UAE: AN INTEGRATED AI ACCEPTANCE-AVOIDANCE MODEL

BY

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Article History

Received: 30/10/2023
Accepted: 06/11/2023
Published: 08/11/2023

Vol – 2 Issue – 11

PP: -61-86

Abstract

Artificial intelligence is accelerating the transformation of accounting processes and operations., but despite the apparent opportunities and advantages, the workforce directly affected by these changes face the main challenge. However, there is limited research on the accountants' perceptions of AI adoption and their willingness to embrace it, particularly in the UAE context. The study addressed this research gap by introducing the Integrated AI Acceptance-Avoidance Model (IAAAM), a comprehensive framework that considers both the benefits and risks associated with AI, as well as the complex relationship between perceptions, attitudes, and behavioral intentions in using AI in accounting. A survey involving 96 accountants in the United Arab Emirates (UAE) was conducted to validate the IAAAM. The empirical findings not only provide insights into accountants' perceptions but also demonstrate the effectiveness of the IAAAM in explaining and predicting their attitudes and behavioral intentions toward AI adoption. While this research contributes to the existing literature, it also reveals a crucial gap between intention and actual usage of AI among UAE-based accountants. This highlights the importance of organizational support infrastructures, enabling technologies, and skill development initiatives to facilitate widespread AI adoption. This research advances academic knowledge as it provides practical guidance to policymakers, academic institutions, professional bodies, and organizations in the UAE in the adoption of AI among accountants in the UAE.

Keywords: *Artificial intelligence, AI adoption in accounting, technology acceptance, attitude towards AI, Unified theory of acceptance and use of technology (UTAUT), Technology threat avoidance theory, (TTAT) Integrated AI acceptance-Avoidance model (IAAAM)*

INTRODUCTION

The proliferation of Artificial Intelligence (AI) presents a profound impact across various domains like e-commerce, healthcare, social media, marketing, education, and agriculture. From facial recognition, virtual chatbots, social media and online shopping personalization, digital marketing optimization to Robotics Process Automation (RPA), AI technologies has integrated into almost any aspect of life with its ability to perform activities that normally require human intelligence and accomplish more complex activities involving cognitive capabilities (Kaplan and Haenlein, 2019). It has become the driving force of a new round of technological innovation and business transformation in various industries, and its potential to transform certainly covers the accounting sector.

Branded for its traditional double-entry system and numerous business processes involving data collection, recording, bookkeeping, month-end closing, financial reporting, audits, endless excel formulas and templates, and other manual processes, the field of accounting proves to be well-suited for the application of AI. Various automations and technologies may have already been employed to improve what accountants do but not all have the intelligence and cognitive ability to be regarded as AI (Kommunuri, 2022). Cognitive technologies, termed to encompass the independent capability of learning overtime and perform tasks as humas do (Onyshchenko *et al.*, 2022), is found to provide enormous benefits to the accounting sector through continuing technological progress like faster and more accurate financial data processing, repetitive tasks automation, and the ability to analyze vast amounts of data which translates to increased efficiency, accuracy, and cost-effectiveness (Cao *et al.*, 2021).

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A study by ICAEW (2018) established that AI can substantially decrease time spent on manual tasks, such as data entry and reconciliation, and enhance accuracy and timeliness of financial information. Similarly, a study by EY Global (2021) presents how AI can provide valuable insights into financial data and automate manual, repetitive tasks, enabling accountants to be more strategic in analysis, and decision-making. Practical applications in the recent years include automated bookkeeping through QuickBooks and Xero, AI algorithms in fraud detection, AI automations in tax compliance, financial forecasting, and audit (Chukwuani and Egiyi, 2020). However, ICAEW (2018) also acknowledges that extensive AI adoption in accounting is still on early stages. The optimistic vision of the future of accounting entails a parallel effort to harness AI's capability to transform the accounting and business landscape but to also understand the perceptions of the professionals working within the sector, whether they are aligned on the conceptual benefits and are onboard to accept the changes and reap practical benefits on the ground.

Conversely, the implementation of AI is not without challenges, as it also foster concerns among professionals about job security, job displacement, upskilling, employability, and well-being as well as ethical issues, and potential bias in decision-making (Stancheva-Todorova, 2019). A study by World Economic Forum (2023) projects net job losses of 14 million from the combined impact of artificial intelligence and socio-economic conditions whereby 83 million jobs are estimated to be displaced and only 69 million jobs created globally in the next five years. The role of the accountant in data entry, record keeping, audit, and reporting may be eliminated and replaced by data analysis and advisory functions with the use of AI. The automation of work can increase efficiency leading to work-life balance; however, the elimination of roles can also translate to a negative implication on job security and employee well-being while the high requirement of new skillsets and expertise brought about by role transformation may create pressure on upskilling and employability. As such, this becomes a strong indication and validation to focus on the professionals working in the accounting sector, be able to explore their practical views, concerns, and challenges, and discover the influences and barriers to their attitude and response to fully adopt and effectively work with intelligent systems.

As the United Arab Emirates (UAE) progresses to be the leading financial hub in the Middle East and North Africa (*Innovation Trends and Report*, 2022), the accounting industry and profession is also rapidly evolving due to its expanding workforce which is made up largely of diverse expatriates. In fact, the UAE aspires to be a global leader in artificial intelligence and has made a strong commitment to developing AI across various industries, including accounting, by announcing initiatives such as the UAE Strategy for Artificial Intelligence 2031 (*UAE Strategy for Artificial Intelligence*, 2017) and the UAE Centre for Fourth Industrial Revolution (*The UAE's Fourth Industrial Revolution (4IR) Strategy*, 2022). Indeed, the country offers a valuable context for assessing AI adoption using the perspectives and attitudes of its accounting professionals.

In this study, the term "accountants" refers to professionals who work in a variety of accounting-related fields, such as general accounting, financial reporting, audit, management accounting, tax, consulting, etc. Perception would refer to a thought, opinion, belief or a way of understanding and interpretation held by accountants based on certain criteria. Response, on the other hand, describes the accountants' attitude and behavioral intentions toward acceptance and use of AI.

Problem statement

Artificial intelligence is rapidly changing the way accounting processes and operations are conducted and while the benefits appear outstanding, it also presents a significant challenge to the workforce who are directly affected by these changes. Accountants are concerned about the lack of knowledge about AI systems, the ease of use, potential errors and bias in decision-making, privacy concerns and ethical implications, and most importantly, the practical impact of AI on their skills (Gambhir and Bhattacharjee, 2021), job security (Peng and Chang, 2019), employment, and well-being (Xu, Xue and Zhao, 2023) and future of work (Brougham and Haar, 2018). Whether these alter the accountants' attitude and intention to adopt AI in their accounting work remains an ongoing concern. Whereas some accountants may have little to no exposure to AI perhaps due to small and medium-sized businesses less likely getting the necessary resources to engage in AI in the UAE, the increasing number of expatriate accountants in the country makes it crucial to analyze awareness and perceptions, to determine how these can affect AI acceptance and adoption and to suggest ways for accountants to prepare for extensive AI integration in the future.

Research questions

This paper will seek to answer the following research questions:

1. What perceptions do accountants in the United Arab Emirates have towards the adoption of artificial intelligence in accounting?
2. How do these perceptions affect the accountants' attitude and response towards the acceptance and adoption of artificial intelligence in accounting?

Research objectives

Above research questions will be guided by the following objectives:

1. To explore how accountants in the UAE view the adoption of artificial intelligence in accounting in terms of usage, relevance, employment and well-being outcomes, and the future of work.
2. Using an integrated AI acceptance and avoidance model, examine whether the perceptions of accountants in the UAE have a positive or negative effect on their attitude and behavioral intention to use artificial intelligence in accounting.

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LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This section seeks to provide an overview of artificial intelligence, analyze recent practical examples and developments of AI applications in accounting, and discuss the implications of adopting it in the accounting field and profession. It will also examine empirical framework of technology acceptance and avoidance and in the end, derive an integrated model that can explain further on the effect of perceptions on the attitude and behavioral intention to use of AI in accounting.

Artificial intelligence in accounting

Origin and concept

The origins of the concept of 'Artificial Intelligence' may be traced back to the 1950s at a conference in Dartmouth College, where it was first used on the idea that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (Zemánková, 2019). Through decades of ups and downs, Martinez (2019) proposed that the definition of AI must be flexible and conceptually changing just as AI continuously transforms its capacity to provide technological breakthroughs and advances.

Haenlein and Kaplan (2019) define artificial intelligence as a system's ability to read and interpret data, learn from it, and apply learnings to achieve particular tasks through flexible adaptation; further classifying it as cognitive, emotional, and social intelligence. According to Chukwudi *et al.* (2018), a system has artificial intelligence if it is capable of performing tasks that a human brain would typically carry out, such as acquiring knowledge. Stancheva-Todorova (2019) similarly agrees that AI encompasses any method that allows computers to mimic human intelligence and may involve machine learning and deep learning, for which Zhang *et al.* (2020) further elaborates that the successful use of big data and machine learning technology to understand the past and predict the future is an evident characteristic of AI. In most definitions, AI is hardware and software that can learn, adapt, analyze, make judgments, and carry-out complex and judgment-based activities in the same manner as the human brain; however, AI can also refer to computer programs, algorithms or systems that demonstrate intelligence (Hasan and Hasan, 2022). Over the years, artificial intelligence became a collective term for the science that is trying to make systems intelligent and while it is usually described through its underlying technology (i.e., machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, fuzzy logic, physical robots), Davenport and Ronanki (2018) suggest that it is beneficial to view AI beyond technology in itself, but also in the context of its capability to address business needs such as process automation, cognitive insights through data analysis, and cognitive engagements with customers and employees; and on the context of this research, see how AI capabilities are changing accounting as an industry, as a function and as a profession.

AI adoption in UAE

McKinsey research within Gulf Cooperation Council (GCC) countries shows that AI has a potential to deliver as much as $150 billion in the region, with 62% of companies in the region using AI in at least one business activity and 23% adopting across multiple business functions (Chandran *et al.*, 2023). Shaer *et al.* (2023) further stated in its research and publication for Mohammed bin Rashid School of Government that the UAE is at the frontline for global digitization, with data, digital transformation, and AI adoption being fundamental pillars in its future vision and strategy for digital development. Furthermore, the research found that AI deployment has been enthusiastically received in both the public and private sectors. Dubai government institutions have high adoption rate and positive impression of AI benefits and impact, with service development operations adopting the most through chatbots or virtual agents and HR, finance, risk, and strategy adopting the least. Despite private sector results indicating favorable sentiments and strong adoption at 54% of the responding organizations using AI through machine learning, virtual assistant, and natural language text comprehension, 82% of the respondents disagreed that AI is vital for organizational success with only 20% claiming benefit at individual business function like product development, marketing, or sales. The research also noted that despite positive findings, both sectors face the same adoption challenges, citing shortage of AI-related skills and talent as the top restrictive barrier and the ambiguous, multi-faceted regulatory and governance environment in the UAE as additional private sector concern. The data suggest that 41% of private sector respondents have fewer than 25% AI-literate staff, and just 28% and 12% of respondents, respectively, have dedicated future AI strategy and implementation plans in next year. The hesitation of companies is evident in lower digital transformation capacity and spending in Dubai compared to global trend and rates, as well as limited access to financing for AI developers. The UAE government heavily invests in upskilling initiatives, talent attraction, and retention through long-term residency opportunities and the creation of UAE Council for Artificial Intelligence to unify numerous regulators and stakeholders for policy making.

Figure 1: AI adoption by business functions - Dubai Private Sector Results (Shaer et al., 2023)

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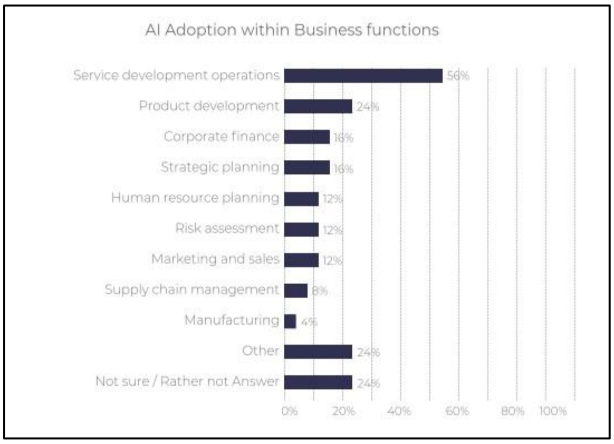

Figure 2: AI adoption by business functions - Dubai Government Sector Results (Shaer *et al.*, 2023)

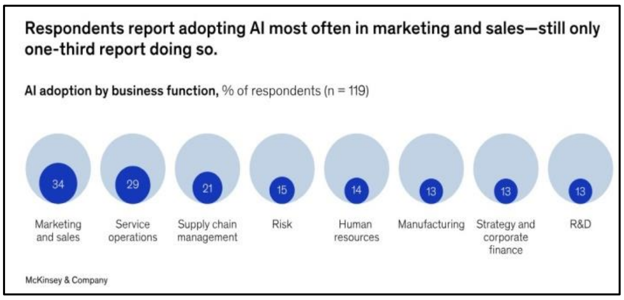

***Figure 3: AI adoption by business functions - GCC countries results* (Chandran *et al.*, 2023)**

Impact and implications of AI in accounting

Four themes emerge from the preceding sections' discussion on AI capabilities and applications, highlighting the potential impact of AI on the accounting sector and profession.

Performance and Productivity enhancements: The advent of AI is continuously changing the traditional accounting function through the automation of routinary, repetitive operational tasks. The ability of AI-automated processes, smart algorithms, and financial robots to simplify data entry, reconciliation, accounting, and financial reporting tasks, increases data accuracy and releases accountants from time-consuming tasks (Li, Haohao, and Ming, 2020) and allows them to focus more on value-adding responsibilities like financial analysis, strategic planning, and client advisory services, that will provide greater value to clients and firm performance (Stancheva-Todorova, 2019). Bughin *et al.* (2017) of McKinsey Global Institute outlined that the automation of routine-intensive activities facilitates productivity growth at the level of individual processes, businesses, and entire economies. Chukwudi *et al.* (2018) further investigated this impact in a descriptive survey and the results presented favorable impact AI have on the productivity of accounting firms in Southeast Nigeria. In a similar study by Bhargava, Bester, and Bolton (2021), employees claim effective time and skill utilization as a result of AI technologies' elimination of low-value and repetitive activities thereby increasing productivity, efficiency, and accuracy at work.

Job displacement: According to research from University of Oxford, there is a 95% likelihood that accountants will lose their employment as machines take over the number crunching and data processing activities (ICAEW, 2019). Frank et al. (2019) refer to it as "technological unemployment" because AI technologies have the potential to result in job obsolescence and displacement. Bughin *et al.* (2017) of McKinsey Global Institute moderately argue stating that only a small number of occupations can be entirely automated by applying AI technologies, while practically all occupations can automate some work activities or functions. Stancheva-Todorova (2019) adds that determining the likelihood for job displacement will require an examination of the end-to-end tasks and activities within accounting, emphasizing that the employment impact is not directed at the entire occupation but rather a defined task or activity. As AI systems become more sophisticated, some routine accounting tasks may be automated, leading to potential job losses for professionals involved in data entry, basic bookkeeping, and transaction processing (Leitner-Hanetseder *et al.*, 2021). However, Bhargava, Bester, and Bolton (2021) drew attention to the fact that the implementation of AI cannot only be seen negatively in terms of the risk it poses to job security, but also in terms of the potential it creates.

Role transformation and the Creation of new tasks and functions: Despite concerns that automation would result in job losses, implementing AI is more likely to result in the transformation of existing roles and the introduction of new functions. Kokina and Davenport (2017) asserted that accounting will be one of the industries that is likely to be augmented by AI technology rather than automated in the next decades, leading to a role or function transformation. Accountants can transition from preparers and processors to roles that require critical thinking, data analysis, and strategic decision-making, leveraging the capabilities of AI to deliver more value-added services. Moreover, the augmentation of accounting roles comes in the form of collaborating with intelligent systems in every aspect; therefore, working with accounting firms, vendors, IT and other organization functions to develop and provide system support is essential (Stancheva-Todorova, 2019). Davenport and Ronanki (2018) posits that as technology advances, AI projects will cost fewer jobs than projected because new job tasks will also develop. Bhargava, Bester, and Bolton (2021) further reiterated that while job losses may be a major consequence of AI implementation with low-skilled workers more vulnerable to unemployment, organizations like the Organization for Economic Cooperation and Development (OECD) and the World Economic Forum (WEF) suggest that job losses can be minimized if job creation is considered. New job tasks for the accountants involve AI project testing and implementation and being internal consultants and strategic advisor within the organization.

Upskilling and adoption of new skills: In a time where AI technologies are slowly replacing human labor in the workplace, it is crucial to have a skilled workforce on the ground. Bhargava, Bester, and Bolton (2021) describes an

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individual's employability as his capacity to satisfy the evolving demands of businesses and their clients, allowing them to reach their full professional potential, so it is really important to develop skills that can keep up with the changes resulting from artificial intelligence. Bughin *et al.* (2017) of McKinsey Global Institute emphasize that as automation from AI technologies intensifies the existing employment gap between high-skill and low-skill workers, the intensity of addressing growing skillset must be prioritized as an industry and as a profession. Shaffer, Gaumer, and Bradley (2020) adds that upskilling and professional development will moderate the impact that is highly seen in the areas of general bookkeeping and accounting, audit, fraud detection, risk management, and inventory management, moderately on tax, financial accounting, and reporting and least on financial planning and management control. Stancheva-Todorova (2019) expands that accountants today need machine learning technical proficiency and the big data analytical skills to support decision-making and help redefine how business operations are conducted. Critical thinking, communication, and leadership skills will be increasingly required to succeed in a technologically advanced environment (ICAEW, 2018); and the need for soft skills like creativity, empathy, judgment, and the capacity to inspire others, as well as for cognitive and emotional abilities like coordination, critical thinking, and complex problem-solving, remain significant (World Economic Forum, 2023). Accounting as a skill and profession will change, necessitating an upgrade in education and qualifications; and because networking and collaboration will play an even larger role in accounting in the future - as humans within organizations and between humans and AI - the technical skill, openness, and flexibility to engage, interact, and work together as humans and robots becomes imperative (Leitner-Hanetseder et al., 2021). Li, Haohao, and Ming (2020) underlines that a transformative environment that fosters learning and growth is a shared responsibility of the individual accountant, academia, professional organizations, the government, and individual business organization.

The presence of evidence regarding companies implementing AI highlights the significance of accountants' perception and acceptance of AI in the accounting field, hence we progress our study focus towards understanding how these perceptions influence or inhibit their overall attitude and willingness to accept and adopt AI.

Perceptions and attitude towards AI in accounting

While the theoretical capabilities and potential implications of AI in accounting have been the topic of numerous research as shown in the preceding sections, considerably less attention has been dedicated to how the affected accounting workforce perceives this, what their overall disposition or inclination is, whether they have a favorable or unfavorable evaluative stance and emotional response and whether or not they want or intend to use it. The Theory of Reasoned Action (TRA) in social psychology asserts that an individual's action and behavior is driven by their own behavioral intention, which sequentially depends on their feelings or attitude about the action and their perception of societal norms (Dwivedi *et al.*, 2019). As such, we investigate the acceptance and adoption behavior of AI in accounting from a human standpoint, taking into consideration UAE accountants' perception and their positive or negative feelings as an emotional and cognitive evaluative response (attitude) about using AI technology.

Brougham and Haar (2018) developed a new measure called Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) awareness to capture workers' attitudes toward the possibility of automation displacing their jobs, and the findings indicate that most workers are optimistic about their careers and the future of work in general, with a strong belief their line of work will continue. Bhargava, Bester, and Bolton (2021) qualitatively explored working adults' perceptions of the effects of robotics, artificial intelligence, and automation (RAIA) on job security, job satisfaction, and employability and discovered that soft skills and decision-making capacity remain essential and irreplaceable, suggesting that technology will have less of an impact on high-level positions than low-level ones and that both organizations and employees need to be ready to evolve with the times and secure their jobs in the future.

Specific to accounting, Chukwudi *et al.* (2018) conducted a study to investigate the impact of AI on the performance of accounting operations in various accounting firms in South East Nigeria. The survey of 185 accountants and managers concluded that AI has a positive impact on how well accounting functions perform, leading to a shift in more decision-making tasks to intelligent systems. Cooper *et al.* (2020) created a similar study interviewing 139 employees and 14 RPA leaders from Big 4 accounting firms to ascertain how the adoption of RPA is affecting work experience within the public industry, and the results show that both groups agree RPA has a positive impact on the profession and enhances work and individual career prospects, but lower-level employees report little to no improvement in work-life balance compared to the significant improvements anticipated by firm executives. Peng and Chang (2019) dedicated another tailored survey to investigate perspectives on AI-driven job displacement among accountants in Taiwan, 70% of respondents believe that AI will predominantly replace manual accounting work primarily in bookkeeping and tax functions, whereas only 32% feel threatened by this development. Rkein *et al.* (2020) likewise executed a qualitative study in Lebanon to determine whether the automation of the accounting profession affects employability, and the findings revealed a high level of awareness and concern among respondents about the outcomes of automation, emphasizing the importance of preparing for it. Results further suggest that while certain accounting occupations may go, new jobs requiring abilities such as critical thinking and consultancy may emerge. Chang, Hsiao, and Peng (2021) also looked into the anxiety and corresponding attitudes accounting professionals have regarding the possibility of losing their jobs in the future. Similarly, their findings indicate that accounting professionals believe not all accounting jobs will be replaced by AI and that

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their work anxiety levels depend on their knowledge of the types of jobs that will be replaced. The perceptions of accounting professionals in Romania with regard to the main advantages and difficulties of AI were also investigated by Banța *et al.* (2022), and the findings indicate that they have a clear understanding of both advantages and difficulties and that AI does not pose a threat to employability, but rather recognizes the need for upskilling. Available studies in the Middle East were specific to the impact of AI within audit. Puthukulam *et al.* (2021) studied how auditors in Oman thought AI affected their professional skepticism and judgment and found that AI and ML-assisted auditing practices have a positive effect on professional skepticism and professional judgment as it aids in detecting errors and material misstatements. Noordin, Hussainey and Hayek (2022) investigated the perceived contribution of AI to the quality of external audits, as well as the disparities between UAE local and international audit firms, believing that the understanding of attitudes and acceptability among external auditors in the UAE allows usage of AI in auditing while also enhancing auditors' technical skills, regardless of the type of audit firm for which they work.

As AI and other automation technologies are projected to grow dramatically in the near future, the perceptions of the affected workforce can have considerable impact on the rate and success of the AI implementation on ground. The researcher endeavors to expand the existing knowledge tailor-fitting it to the accounting professionals in the UAE.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The acceptance and adoption of new information systems and technological advancements like artificial intelligence, has long been an interest in research and practice. With the dynamic nature of technology, many theories and models have been established and refined over time to elucidate and predict its adoption. Technology adoption, according to Granić (2023), is the process of accepting, integrating, and embracing new technology to fully utilize it, whether at individual or organizational level. The Technology Acceptance Model (TAM) is among the well-established research model on the individual acceptance of new technology, and several extension studies observing the intention and use behavior of new technologies employ this fundamental model of acceptance, particularly Unified Theory of Acceptance and Use of Technology (UTAUT) which is one of the theoretical source of this paper. Proposed by Fred Davis in 1986, TAM is a variation of Theory of Reasoned Action (TRA) that was tailor-fitted to model the determinants of the behavior behind user acceptance of information systems (Davis, 1986). Furthermore, TAM's key goal to understand user acceptance processes and model theoretical relationships among fundamental influencing variables is based on TRA's generic behavioral concept that attitude and subjective norms influence behavioral intention, which in turn directs human behavior and action. TAM promotes two primary concepts as direct predictors system use behavior: perceived usefulness (PU) and perceived ease of use (PEOU). Fayad and Paper (2015) recaps that the model believes that people form intentions to engage in behaviors that they have a positive affect or attitude, which results from a cognitive appraisal of how a system will be useful to enhance performance (PU) and how a system is easy to use and interact with (PEOU). On a more fundamental level, it is held that the formulation of an intention to perform a behavior is a prerequisite for the behavior to occur (Granić, 2023), and that the user's perception of effectiveness is higher when the system is easier to use (Peng and Hwang, 2021). However, due to its narrow applicability and construct antecedents that ignored other innovation domains and external social influences, the two-factor TAM's simplicity and predictability were criticized and challenged, leading to numerous theoretical extensions over the years (Marikyan and Papagiannidis, 2023). The extension and progression of theoretical models that explains the determinants or constructs of technology acceptance at an individual level has been briefly summarized by Mishra and Sharma (2014) in **Figure 5** below.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model in **Figure 6** proposed by Venkatesh *et al.* (2003) is regarded as broadly encompassing in assessing individual technology acceptance because it uses the behavioral model of TAM as a theoretical foundation, synthesizing a large number of constructs and propositions from eight previously established models above to create a unified model that reflects the most applicable determinants for complex system usage (Dwivedi *et al.*, 2019). Zuiderwijk, Janssen, and Dwivedi (2015) attributed the work of Venkatesh *et al.* (2003) in its validation of computer software adoption and usage by American workers, highlighting that UTAUT surpassed other models because it accounted 70% of the variance in adoption behavior compared to 40% explained by older models. The commonality in all these models is the behavior i.e., the use of new technology.

Year	Theory/Model	Developed By	Constructs/ Determinants of adoption
1960	Diffusion of Innovation Theory	Everett Roger	The innovation, communication channels, time and social system.
1975	Theory of Reasoned Action	Ajzen and Fishbein	Behavioural intention, Attitude (A), and Subjective Norm.
1985	Theory of Planned Behaviour	Ajzen	Behavioural intention, Attitude (A), and Subjective Norm, Perceived Behavioural Control.
1986	Social Cognitive Theory	Bandura	Affect, anxiety.
1989	Technical Adoption	Fred D Davis	Perceived usefulness and perceived ease of use.
1991	The Model of PC Utilization	Thompson et al.	Job-fit, Complexity, Long-term consequences, Affect Towards Use, Social Factors, Facilitating Conditions.
1992	The Motivation Model	Davis et al.	Extrinsic motivation (such as perceived usefulness, perceived ease of use, and subjective norm) and intrinsic motivation (such as perceptions of pleasure and satisfaction).
2000	Extended TAM2 model	Venkatesh and Davis	Social influence processes (subjective norm, voluntariness and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability and perceived ease of use).
2003	Unified Theory of Acceptance and Use of Technology (UTAUT)	Venkatesh et al.	Performance expectancy, effort expectancy, social influence and facilitating conditions.

Figure 4: Evolution of Theories and Models of Technology Adoption **(Mishra and Sharma, 2014)**

The central tenet of UTAUT, according to Venkatesh *et al.* (2003), is that actual usage behavior is directly determined by behavioral intention in conjunction with facilitating conditions, whereas performance expectancy, effort expectancy, and social influence directly influence behavioral

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intention to use and indirectly behavioral use. Gender, age, experience, and voluntariness of use were established as key moderators of the effect of the four constructs, increasing the model's predictive potential. Cao *et al.* (2021) summarizes that the model intends to justify user intentions towards technology use and the usage behavior under a voluntary circumstance.

Performance Expectancy (PE), the new term used in UTAUT that corresponds to perceived usefulness (PU) in TAM model, is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003).

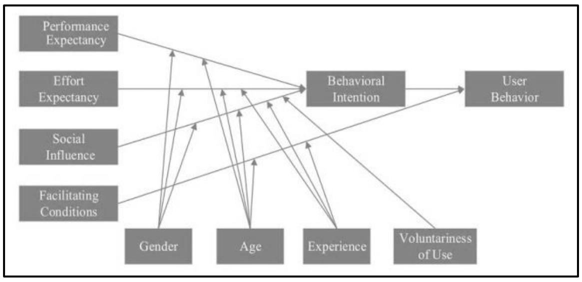

Figure 5: The unified theory of acceptance and use of technology (UTAUT) Model **(Venkatesh *et al.*, 2003)**

For Venkatesh, Thong and Xu (2016), this is the strongest predictor of usage intention in both mandatory and voluntary circumstances, and this is corroborated by Michel, Bobillier-Chaumon and Sarnin's (2014) findings on the managers' attitude toward using social media for innovation processes, Baptista and Oliveira's (2015) research on understanding mobile banking acceptance and Peng and Hwang's (2021) study on Taiwanese e-learning social media platform adoption. Faizal, Jaffar, and Mohd nor (2022) directs that perception of valued outcomes and benefits enhances the motivation for using a certain technology. Furthermore, Chow *et al.* (2023) views PE as the substantial rewards for users who benefit from greater efficiency and convenience out of technology usage.

Effort Expectancy (EE) is defined the lack of physical or mental effort to use and operate a particular technology or simply the ease of use (Venkatesh *et al.*, 2003). With comparable definition and scale, this correlates to Perceived Ease of Use (PEOU) in the TAM Model. Peng and Hwang (2021) added that when a system is simpler to use, users are more likely to find it beneficial and useful and are more likely inclined to accept a particular technology. Zuiderwijk, Janssen, and Dwivedi (2015) claim that when a system is difficult to use and the performance gains can be overshadowed by the effort of using it, users' skills and learning capacity can mitigate system complexity.

Social Influence is defined as the "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh *et al.*, 2003). This construct depicts the influence of other people's opinions and actions toward a certain user behavior, which can originate from management or office leaders, family, close friends, colleagues, or other influential persons directly engaged in a particular activity. Momani (2020) reechoes the findings of Venkatesh *et al.*, (2003) that this construct is most relevant and strongest in a mandatory implementation of technology, which is also supported by various healthcare studies by Choudhury (2022) and Macdonald, Perrin, and Kingsley, (2020).

Facilitating Condition is defined as "the degree to which an individual believes that an organization's and technical infrastructure exists to support the use of the system" (Venkatesh *et al.*, 2003). Holden and Karsh (2010) expound that this encompasses infrastructure, internal or external resource limits, as well as the skills, resources, and opportunities required to operate the system. The model suggests that this component directly affects use behavior rather than intention to use and that users who have access to good facilitating conditions are expected to have greater utilization results (Baptista and Oliveira, 2015).

With several research using the UTAUT model thoroughly throughout time to improve its predictive capacity in the context of technology and beyond, UTAUT has undoubtedly made major contributions to the literature. It has been used across multiple areas of discipline and research topics like consumer health technology (Holden and Karsh, 2010), mobile banking (Baptista and Oliveira, 2015), open data technology (Zuiderwijk, Janssen and Dwivedi, 2015), consumer acceptance (Venkatesh, Thong and Xu, 2016), cloud computing (Nikolopoulos and Likothanassis, 2017), e-health (Macdonald, Perrin and Kingsley, 2020), e-learning (Lim *et al.*, 2021) and digital technologies (Faizal, Jaffar and Mohd nor, 2022). Although UTAUT gained solid reputation for technology acceptance assessment, the model is criticized for having numerous independent variables complicating the evaluation of technology intention and behavior (Granić, 2023) and its incapacity to justify behavioral intent in various contexts as practical applicability (Momani (2020). Dwivedi *et al.* (2019) argues that voluntariness of use as a moderator limits the model's applicability to cases where an organization mandates adoption of a system or technology, leaving users no option but to comply, and that facilitating conditions may need to be completely reconsidered to predict behavioral intention to align to prior acceptance theories. Furthermore, the measurement capability of the model is viewed as incomplete because it does not take into account negative impact and avoidance factors, it is less personal in the absence of consideration of personal concerns resulting from implementation outcomes (Cao *et al.*, 2021) and the required individual characteristics to engage in usage behavior (Dwivedi *et al.*, 2019).

To the best of the author's knowledge, few accounting studies have utilized UTAUT such as AI adoption in audit in Australia (Yang, Blount, and Amrollahi, 2021), blockchain in accounting (Abu Afifa, Vo and Le, 2022), and digitalization in accounting (Taib *et al.*, 2022). Because the subject of UTAUT now appears to focus on the advent of new digital technologies (Wang *et al.*, 2022), it will be interesting to use and expound the model in the concept of AI adoption in the

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field of accounting in the UAE. The expansion of which is expected to boost the reliability of the model

Technology Threat Avoidance Theory (TTAT)

Technology possesses the capacity and potential to augment individual and organizational performance, while also harboring the susceptibility and propensity to be exploited in ways that pose risks and threats to users. A broader perspective must consider technology to have detrimental impact on users due to a variety of concerns, including trust, security, fears, risk, and wellbeing (Agogo and Hess, 2018). While positive impact encourage technology acceptance, Liang and Xue (2009) argue that avoidance is a distinct phenomenon that the previously stated adoption models may be unable explain. Cao *et al.* (2021) observes that there appears to be less research on the factors that affect an individual's intention to avoid technology than there is on enhancing adoption and diffusion. One of the most frequently referenced literature models is Technology Threat Avoidance Theory (TTAT) shown in **Figure 7**.

The model seeks to identify user perceptions and motivations that will explain and justify the avoidance of IT threats in voluntary settings. Carpenter *et al.* (2019) elaborates that TTAT presents an encompassing framework that substantiates underlying factors influencing threat avoidance behavior and elucidates the cognitive processes individuals employ to assess threats, cope with them, seek resolutions, and eventually avoid it through safeguarding measures. Simply put, TTAT's key concept is that individuals avoid malicious technology when they perceive a threat and believe they can effectively evade it through precautionary measures (Liang and Xue, 2009).

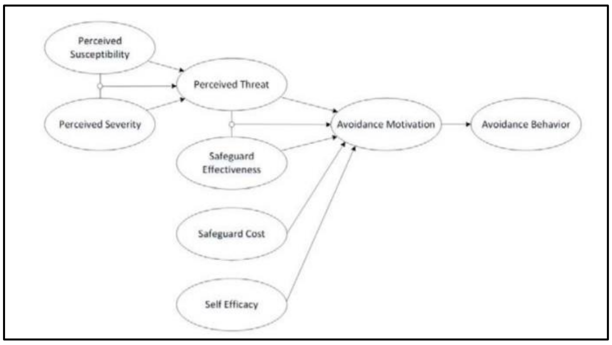

***Figure 6: Technology Threat Avoidance Theory (TTAT)* (Liang and Xue, 2010)**

Moreover, Liang and Xue (2010) tested their theory and presented in the model that technology threat avoidance behavior is driven the motivation to avoid such threat, which is in turn influenced by their perception of the level of threat. These threat perceptions are driven by the perceived likelihood of the threat occurring (susceptibility) and the perceived severity of the threat's negative repercussions, and their interaction. Additionally, three constructs, namely safeguard effectiveness, safeguard cost, and self-efficacy have an impact on the avoidance motivation. Safeguard effectiveness is described as the individual evaluation on the effectiveness of the safeguarding measure to avert the technology threat. Safeguard cost refers to the physical and cognitive effort necessary to implement safeguard measure. Finally, self-efficacy refers to the individuals' confidence in implementing the safeguard measure. TTAT model has been verified by prior studies in varying extents and context like online phishing (Arachchilage and Love, 2014), biometric identity authentication (Breward, Hassanein, and Head, 2017), cybersecurity solutions (Carpenter *et al.*, 2019b), social media e-learning (Peng and Hwang, 2021) and AI for decision-making (Cao *et al.*, 2021). Relevant to our study is the consistency of the findings that individual threat perception influences the user response toward technology usage.

Gaps in literature and conclusion of literature review

The literature review explained the concept of AI, its capabilities, potential impact, and implications in general and specific to the field of accounting. This sets the expectation that the substantial growth in AI technologies in the foreseeable future highly depends on the response of the affected workforce. The limited AI adoption in Dubai in most functions including finance, as revealed in the latest Mohammed bin Rashid School of Government research by Shaer *et al.* (2023), indicates that the impact and ramifications of AI are predominantly theoretical rather than practical at present.

The review further revealed certain gaps and limitations that we find relevant to be addressed in this research. First, there appears to be a lack of research into how accounting professionals in the UAE perceive AI adoption and its implications and whether or not they intend to use it. Second, despite the pervasive adoption of UTAUT theory, few studies are known to have applied UTAUT to the acceptance of artificial intelligence in the UAE accounting industry. Thirdly, our research challenges the measurement capability of the UTAUT model as insufficient because it fails to account for the negative impact and avoidance factors, lacks consideration of personal concerns arising from implementation outcomes (Cao et al., 2021), and overlooks the required individual characteristics for engaging in usage behavior (Dwivedi et al., 2019). Therefore, to address the identified gaps and contribute to the existing literature on AI in accounting, this research seeks to provide empirical evidence of UAE accountants' perceptions on AI adoption. It seeks to solidify the conceptual relationship between perception and willingness to use to promote adoption at an individual practical level.

1.1. Conceptual research model and hypothesis

To accomplish the research objective and address the aforementioned identified gaps, a conceptual model is formulated and tested in this research to elucidate the relationship between accountants' perceptions to their attitudes and behavioral intentions to use artificial intelligence in accounting. **Figure 8** shows the proposed integrated AI acceptance-avoidance model that draws upon theoretical concepts from UTAUT and TTAT, identify unique influencing factors to AI acceptance, and consolidate determinants and variables at a high-level context.

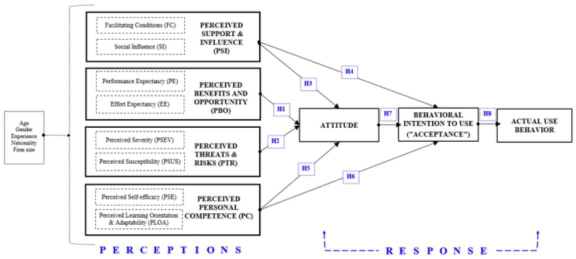

Figure 7: Integrated AI acceptance-avoidance model developed by the author (IAAAM)

The following considerations were made in the development of the conceptual model and hypothesis:

- *Integration of both technology acceptance and avoidance factors* - Technology possesses the capacity and potential to augment individual and organizational performance, but also have the susceptibility and propensity to be exploited, posing risks and threats to users. A broader perspective must consider technology to have detrimental impact on users due to a variety of concerns, including trust, security, fears, risk, and wellbeing.
- *Incorporating a value-based perspective* – The perceived value of AI in this study is a combination of the benefits and opportunities from performance and effort expectations, employment, and wellbeing outcomes, as well as the perceived threats and risks associated with AI adoption (Youn and Lee, 2019). The affected workforce can evaluate the value they derive, leading to a more precise determination of their intention to use the new technology (Liao et al., 2022).
- *Simplification through high-level constructs* – Grouping AI acceptance determinants reduces complexity in hypothesis derivation and testing. Perceived support and influence (PSI) refer to the facilitation of conditions and social influence that primarily come from external sources like the workplace. Potential positive outcomes are under perceived benefits and opportunities (PBO), while potential negative consequences are under perceived threats and risk (PTR). Perceived personal capability (PBC) encompasses an individual's self-efficacy, learning orientation, and adaptability.
- *Personal approach* – The proposed research model considers human perceptions, concerns, and attitudes to acknowledge the collaboration between humans and AI. Although UTAUT does not incorporate attitude as determinant in usage behavior, our model aligns with TRA and the original TAM model in suggesting that individuals develop intentions to engage in behaviors that they perceive positively and have a favorable attitude towards. Attitude represents overall disposition, inclination, and encompassing emotions which involves evaluative, cognitive, and motivational judgments towards AI adoption (Gkinko and Elbanna, 2022). Moreover, personal competence is important because it can promote the adoption of AI while minimizing stress and anxiety. This is achieved by cultivating self-confidence, proficiency, a propensity for learning, and adaptability.

By employing this integrated approach, a more comprehensive understanding of AI acceptance and avoidance in the UAE accounting sector can be achieved. The variables within the conceptual model are enumerated and defined within the scope of this paper, as presented in **Table 1** in the **Appendix** section. The following hypotheses are proposed for this paper:

***H_1**: Perceived benefits and opportunities will have a significant positive effect on the accountants' attitude towards AI in accounting.*
***H_2**: Perceived threats and risks will have a significant negative effect on the accountants' attitude towards AI in accounting.*
***H_3**: Perceived support and influence will have a significant positive effect on the accountants' attitude towards AI in accounting.*
***H_4**: Perceived support and influence will have a significant positive effect on the accountants' behavioral intention to use AI in accounting.*
***H_5**: Perceived personal competence will have a significant positive effect on the accountants' attitude towards AI in accounting.*
***H_6**: Perceived personal competence will have a significant positive effect on the accountants' behavioral intention to use AI in accounting.*
***H_7**: Attitude has a significant positive effect on the accountants' behavioral intention to use AI in accounting.*
***H_8**: Behavioral intention to use AI in accounting has a significant positive effect on the accountant's actual use of AI in accounting.*

RESEARCH DESIGN

Philosophy and Approach

Research Approach: This study will apply a deductive approach which starts with a theory or general knowledge base and then the formulation of hypothesis which is afterwards tested using empirical data.

Research Methodology: The research choice will use a mono-method approach, specifically utilizing the quantitative research methodology. Quantitative methods place an emphasis on objective measurements via numerical or statistical analysis. This method of data collection aids in either confirming or refuting the research question and can be replicated depending on scope or criteria. This particular research employs structured survey questionnaires to gain insights from observations, facilitating the comparison of various perspectives through the collected empirical data. The research will be descriptive as it examines the awareness and perceptions; as well as analytical as it establishes relationship between perception towards attitude and behavioral intention to use AI in accounting.

Research Strategy: The study will employ a survey research strategy, which involves collecting data from a sample of

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accounting professionals working in the UAE using a structured questionnaire. This strategy is suitable for efficiently gathering a substantial amount of data within a limited timeframe, which will be utilized to address the research questions. Survey strategy is frequently associated with the deductive approach and is frequently employed in quantitative research projects involving the selection of a representative of the population.

Data collection and research instrument

Sampling: This research employs a non-probability sampling method that combines convenience sampling with exponential non-discriminative snowball sampling technique. Convenience sampling is a method of participant selection that relies on accessibility and willingness to participate. The target sampling population are the accountants working in various function, organization, or industry in the UAE. This study has primary data by using a structured questionnaire to survey accountants employed in the UAE. The term "accountants" encompasses any professional who work in a variety of accounting-related fields, such as general accounting, financial reporting, audit, management accounting, tax, and consulting among others. While the approach may be appropriate and convenient, sampling selection bias is unavoidable and can lead to unequal opportunities for participation and may not provide accurate representation of the entire population of accountants in the UAE. Due to constraints in time and resources, the research has a target sample size of 96 participants.

The survey questionnaires were administered online using Google Forms. The researcher shared the questionnaire link with accountants in her network, who then passed it on to their colleagues and other accountants. Participants were also invited to complete the questionnaire via professional networks on LinkedIn, other social media platforms, and accounting groups and forums. The responses were directly consolidated using Google sheets for purposes of analysis by the researcher.

Nature of data and Measures: Data options in this research is mainly categorical. Nominal data were collected in the demographics or individual characteristics section of the questionnaire. The data collected in section 3 which assessed awareness, is categorized as nominal dichotomous due to the utilization of a binary "Yes/No" response format. In section 4, accountant's perceptions, attitude, and behavioral intentions toward the application of AI in accounting were evaluated using a 5-point Likert scale format (ranging from 1-strongly disagree to 5-strongly agree), which is considered ordinal in nature because it involves ranking or ordering responses according to a predetermined scale. Acknowledging the importance of consistent measures and methods of analysis for facilitating comparability across research, the survey questions and measures were a derived from previously validated questionnaires of technology acceptance and avoidance, tailored to the subject and the logistics of the research. There are four identified key latent independent variable used in this study in the form of categorical perceptions from accountants in the UAE. Dependent variables in this study are the resultant attitude and the usage behavior as presented in our conceptual research model in Figure 8 above. Ultimately, the questionnaire consisted of 43 items in total, categorized in the following sections: demographics (7), awareness assessment (2), independent variables (26), and dependent variables (8). **Table 1** below presents a summary table of the questionnaire design showing the constructs, indicator, measures, and scales. **Appendix 2** of this paper shows the survey questions for each item indicator along with the references from which they were adopted.

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Table 1: Questionnaire design (constructs, measures, and scale)

Variables or construct	Item indicator	Acronym	Scales
Demographics (D)	Gender	G	Male (1), Female (2), Prefer not to say (3)
	Age	A	21-30 (1), 31-40 (2), 41-50 (3), 51-60 (4), 61 and above (5)
	Highest level of education	HE	PHD (1), Masters/Postgraduate (2), Bachelor's degree (3), Diploma (4), Professional certification (5)
	Area of accounting they are currently working	AA	General accounting/Financial accounting & reporting (1), Internal audit (2), External Audit (3), Management accounting (4), Tax accounting (5), Advisory/Consulting (6), Other (7)
	Years of work experience as accountant	Y	Less than 1 year (1), 1-3 years (2), 4-6 years (3), 7-10 years (4), Over 10 years (5)
	Company headcount	HC	1-10 employees (1), 11-50 employees (2), 51-250 employees (3), 251-500 employees (4), More than 500 employees (5)
	Nationality category	N	Arab (1), Asian (2), African (3), Western (4), European (5), Other (6)
Awareness (AW)	Awareness assessment	AW1	Yes, I have good knowledge and understanding of AI applications in accounting (1) I have heard about AI in accounting, but I would like to learn more (2) No, I am not aware of AI being used in accounting (3)
	Primary source of knowledge	AW2	Academic studies (1), Professional development courses or certifications (2), Professional bodies and Industry conferences and seminars (3), Conversations with colleagues or industry professionals (4), Hands-on usage of AI applications in the workplace (5), Online articles and publications (6), social media (7), Not aware or not exposed (8)
Perceived Benefits and Opportunities (PBO)	Performance expectancy or Perceived usefulness	PBO-PE	Likert scale 1 to 5 (Strongly disagree to Strongly agree)
	Effort expectancy or Perceived ease of use	PBO-EE	
	Perceived opportunity	PBO-O	
Perceived Threats and Risks (PTR)	Perceived severity	PTR-PSEV	
	Perceived susceptibility	PTR-PSUS	
Perceived Support and Influence (PSI)	Perceived social influence	PSI-SI	
	Perceived facilitating conditions	PSI-FC	
Perceived Personal Competence (PPC)	Perceived self-efficacy	PPC-SE	
	Perceived learning orientation and adaptability	PPC-PLOS	
Attitude (ATT)	Attitude towards using	ATT	
Behavioral Intention (BI)	Behavioral intention to use	BI	
Actual use (AU)	Actual use	AU	Yes (1), No (2)

Approach to Data Analysis

The study will use descriptive and inferential statistical analyses to analyze the data collected through the questionnaire. Descriptive statistics will summarize participants' responses, while multiple regression analysis and correlation analysis will test the research questions and hypotheses generated from the theoretical framework to determine the relationships between independent and dependent variables. This method of data analysis is appropriate for investigating perceptions, attitudes, and behavioral intention toward AI and identifying any relationships or associations between the variables of interest. The SPSS (Software Package for Social Science) software will be utilized.

Limitations of the study

The research survey is carried out within defined circumstances known to the researcher. In this instance, the time constraint of four weeks limited survey respondents to those within the researcher's network. A broader and more diverse pool of participants would have facilitated a more comprehensive representation of the findings. A minimum of 70 respondents was required for data analysis to commence.

DATA COLLECTION AND ANALYSIS

This chapter will present and analyze the research survey findings using IBM SPSS software. The first part will present participant demographics and discuss the perceptions of accountants in the UAE regarding the adoption of AI in accounting in terms of usage, relevance, employment and well-being outcomes, and the future of work. The results of the correlation and regression analyses will then be discussed to address the second research objective of assessing the impact of accountants' perceptions on their attitude and behavioral intention to use AI in accounting.

Results and Findings

Respondent information

Data collection was administered between July 14 to August 7, 2023, with a target of 70 participants. Out of the 102 participants who responded to the survey, 6 responses were ineligible as they were submitted by non-accountants. Only 96 respondents were included in the final analysis, meeting the desired sample size. **Table 2** summarizes the demographic characteristics of the respondents categorized by their gender, age, years of work experience, company headcount, and nationality, among them.

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Table 2: Demographics of survey respondents

Demographic variable	Option	Respondents	Percentage (%)
Gender	Male	45	46.9%
	Female	51	53.1%
Age	21-30	19	19.8%
	31-40	45	46.9%
	41-50	30	31.3%
	51-60	1	1%
	61 and above	1	1%
Years of work experience	Less than 1 year	3	3.1%
	1-3 years	0	0.0%
	4-6 years	14	14.6%
	7-10 years	28	29.2%
	Over 10 years	51	53.1%
Company headcount	1-10 employees	7	7.3%
	11-50 employees	22	22.9%
	51-250 employees	32	33.3%
	251-500 employees	15	15.6%
	> 500 employees	20	20.8%
Nationality	Arab	12	12.5%
	Asian	53	55.2%
	African	13	13.5%
	Western	2	2.1%
	European	16	16.7%

Females make up 53.1% of the sample, while males account for 46.9%. The primary age groups consist of individuals between the ages of 31 and 40, accounting for 46.9%, and those between the ages of 41 and 50, accounting for 31.3%. A considerable majority of respondents (53.1%) have more than ten years of work experience, and there is representation across several firm headcount categories, with 51-250 people being the most prevalent (33.3%). With respect to nationality, the majority (55.2%) are Asian, with Europeans (16.7%) and Africans (13.5%) following closely after.

Survey participants were allowed multiple responses for their level of education and the current accounting function they perform, and based on this multiple response options, the survey results in **Table 3** indicate that the majority of individuals surveyed possess a Bachelor's degree (46.80%), and a similar percentage possess Professional Certifications (46%), while a smaller proportion have obtained Master's/Post-graduate degrees (7.20%), with no reported PhD holders.

Table 3: Demographics of survey respondents – Highest level of Education

Level of education	Responses		
	N	Percent	Percent of cases
PHD	0	0%	0%
Master's/ Post-graduate	10	7.2%	10.4%
Professional Certification (CPA, ACCA, CMA, etc.)	64	46.0%	66.7%
Bachelor's degree	65	46.8%	67.7%
Total	139	100%	144.8%

Table 4 shows that majority of the respondents are currently engaged in General Accounting/Financial Accounting and reporting functions (51.9%), followed by Management Accounting (24.1%), and External Audit (15.7%), among others. The survey findings indicate that a small proportion (8.3%) of participants claim to possess a strong understanding of AI applications in accounting, while 11.5% acknowledge their lack of awareness and exposure. A significant 80.2% of the participants were aware but expressed a strong desire to gain more knowledge on the subject.

Furthermore, the survey received 242 responses from 96 participants in terms of the different channels where they learn about AI's potential in the accounting domain in **Table 5**. The results show that social media (27.3%) and online articles/publications (12.4%) have significant roles in raising awareness as these digital platforms provide easily accessible information and have become modern influences nowadays.

Table 4: Demographics of survey respondents – Current accounting function performed

Accounting function	Responses		
	N	Percent	Percent of cases
General Accounting / Financial Accounting & Reporting	56	51.90%	58.30%
Management Accounting	26	24.10%	27.10%
External Audit	17	15.70%	17.70%
Tax Accounting	5	4.60%	5.20%
Advisory/Consulting	3	2.80%	3.10%
Internal Audit	1	0.90%	1.00%
Total	108	100.0%	112.5%

Conversations with colleagues and industry professionals (25.2%) also emerge as a prominent source, underlining the

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importance of peer interactions and industry networking in knowledge sharing. Moreover, the significance of formal education and specialized training in acquiring knowledge is highlighted by professional development opportunities such as courses or certifications (8.3%), participation in professional bodies and industry events (9.5%), and engagement in academic studies (6.2%). Only a small percentage of individuals engage in practical learning at work, such as workplace training (4.1%) and using AI application hands-on (2.5%).

Table 5: Sources of awareness on AI usage in accounting

Source of awareness and knowledge	Responses N	Responses Percent	Percent of cases
Social media	66	27.3%	68.8%
Conversations with colleagues or industry professionals	61	25.2%	63.5%
Online articles and publications	30	12.4%	31.3%
Professional bodies and Industry conferences and seminars	23	9.5%	24.0%
Professional development courses or certifications	20	8.3%	20.8%
Academic studies	15	6.2%	15.6%
Not aware or not exposed	11	4.5%	11.5%
Workplace training only with no hands-on experience	10	4.1%	10.4%
Hands-on usage of AI applications in the workplace	6	2.5%	6.3%
Total	242	100.0%	252.1%

2.1.1 Perception on AI adoption in accounting

The study analyzed seven variables, including their determinants and items, to gain understanding of the participants' perspectives on the usage, relevance, impact on employment and well-being, and future implications of AI in accounting. **Table 6** below summarizes key statistical indicators such as mean, standard deviation, skewness, and kurtosis, to provide insights into the distribution characteristics of the data.

Perceived Benefits and Opportunities (PBO) comprise three key dimensions: Performance Expectancy (PE), Perceived Ease of Use (PEOU), and Perceived Opportunity (O). The survey participants showed a generally positive inclination towards adopting AI in accounting (M=3.75, SD=0.56). This was particularly evident for "PBO.2.PE" (M=4.34), where 44% strongly agreed and 48% agreed that implementing AI would relieve them from routine tasks, allowing them to focus on more value-adding tasks, and “PBO.1.PE” (M=3.94), where 13% strongly agreed and 74% agreed that AI can enhance productivity and job performance. These findings suggest that respondents recognize the practical effectiveness and relevance of AI in their roles. Results further suggest that participants are moderately positive about the ease and flexibility of using AI in accounting (M=3.39, SD=0.79), although a greater variability in perceptions can be noted in a higher standard deviation of 0.79 compared to PBO-PE. The average Perceived Opportunity agreement across all questions is 3.73. The results for "PBO.7.O" (M=4.91) significantly supported the premise that the future of accounting work requires collaboration between human accountants and AI. The results for "PBO.8.O" (M=4.06) show that AI in accounting promotes new abilities and competencies. While participants' opinions on AI's impact on employment opportunities were relatively neutral (M=2.91), only a small percentage (4%) strongly disagreed and 40% disagreed. However, respondents perceived the use of AI as a chance to improve job engagement and future career prospects in the context of "PBO.9.O" (M=3.97). All three dimensions distributions exhibited negative skewness, implying a tendency towards higher ratings on the scale and suggesting that participants may hold more positive opinions regarding the overall PBO dimension.

Another key variable, *Perceived Threats and Risks (PTR)*, has two dimensions: Perceived Severity (PSEV) and Perceived Susceptibility (PSUS). The aggregate findings in this construct indicated that participants hold moderately balanced perceptions regarding the threats and risks associated with AI in accounting (M=3.38, SD=0.671). This implies that while accountants recognize the risks, they don’t consider them as extremely severe (M=3.63) or themselves as highly vulnerable to these risk (M=3.13). The highest level of agreement was found for the statement "PTR.4.PSEV" (M=4.03, SD=0.88). Specifically, 35% of respondents strongly agreed and 36% agreed that job polarization is likely, with the emergence of specialized AI-related accounting roles. According to "PTR.3.PSEV" (M=3.36, SD=1.05), participants are somewhat in agreement that AI will eventually replace human accountants. Accordingly, the results show a moderate level of anxiety regarding the demands for upskilling in "PTR.5.PSUS" (M=3.27), job displacement in "PTR.6.PSUS" (M=3.10), and decreased employment prospects in "PTR.7.PSUS" (M=3.30). Despite perceived susceptibility, participants are least concerned about the extent of worry regarding AI threats and risks, with 7% strongly agreeing and 30% agreeing in "PTR.8.PSUS" (M=2.85, SD=0.96). The slightly negative skewness can point to a more cautious or negative perceptions.

The third key variable in this study, *Perceived Support and Influence (PSI)*, has two dimensions: Facilitating Conditions (FC) and Social Influence (SI). These dimensions represent how participants perceive external factors and social pressures affect their AI adoption decisions. Accountants exhibited a moderately neutral stance (M=3.09, SD= 0.67) regarding the influence of external factors on AI adoption. Additionally, they perceive moderate facilitating conditions for its adoption (M=2.95, SD=0.91). The highest agreement was observed for "PSI.2.SI" (M=3.24), with 46% of respondents saying that they are influenced by the proportion of coworkers using AI. Participants also believe that their peers and others around them moderately endorse the use of AI in accounting (M=2.95, SD=0.91). Accountants generally perceive their organization and senior management as supportive of using AI in "PSI.4.FC" (M=3.20), with observed variations in responses (SD=1.05). However, they are relatively uncertain about the availability and accessibility of resources, technical assistance, support, and training for AI adoption in accounting, as indicated by the results for "PSI.3.FC" (M=2.70, SD=0.96). The skewness values indicate a distribution that is relatively symmetric, as they are close to zero.

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Table 6: Descriptive Statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis		% of responses				
Code	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
PBO.1.PE	96	3.94	0.68	-1.79	0.25	6.79	0.49	2%	1%	10%	74%	13%
PBO.2.PE	96	4.34	0.81	-1.82	0.25	5.04	0.49	2%	1%	5%	44%	48%
PBO.3.PE	96	3.81	0.76	-1.15	0.25	2.99	0.49	2%	2%	21%	63%	13%
PBO_PE_avg	96	3.78	0.62	-1.33	0.25	3.98	0.49	2%	1%	12%	60%	24%
PBO.4.EE	96	3.47	0.78	-0.64	0.25	0.26	0.49	1%	10%	33%	51%	4%
PBO.5.EE	96	3.31	0.97	-0.53	0.25	-0.88	0.49	2%	25%	17%	52%	4%
PBO_EE_avg	96	3.39	0.79	-0.51	0.25	-0.13	0.49	2%	18%	25%	52%	4%
PBO.6.O	96	2.91	1.01	0.13	0.25	-1.12	0.49	4%	40%	21%	32%	3%
PBO.7.O	96	4.19	0.70	-1.03	0.25	3.27	0.49	1%	0%	10%	56%	32%
PBO.8.O	96	4.06	0.63	-1.08	0.25	5.15	0.49	1%	0%	10%	69%	20%
PBO.9.O	96	3.97	0.64	-1.20	0.25	4.87	0.49	1%	1%	13%	71%	15%
PBO.10.O	96	3.50	0.92	-0.58	0.25	-0.41	0.49	1%	18%	20%	53%	8%
PBO_O_avg	96	3.73	0.58	-0.97	0.25	3.95	0.49	2%	12%	15%	56%	16%
PBO_avg	96	3.75	0.56	-1.31	0.25	4.99	0.49	2%	10%	17%	56%	15%
PTR.1.PSEV	96	3.49	0.77	-0.82	0.25	-0.37	0.49	0%	15%	24%	59%	2%
PTR.2.PSEV	96	3.64	0.81	-0.82	0.25	0.06	0.49	0%	14%	17%	63%	7%
PTR.3.PSEV	96	3.36	1.05	-0.17	0.25	-0.88	0.49	2%	23%	25%	36%	14%
PTR.4.PSEV	96	4.03	0.88	-0.45	0.25	-0.74	0.49	0%	4%	24%	36%	35%
PTR_PSEV_avg	96	3.63	0.65	-0.42	0.25	-0.33	0.49	1%	14%	22%	49%	15%
PTR.5.PSUS	96	3.27	0.92	-0.32	0.25	-0.97	0.49	1%	25%	24%	46%	4%
PTR.6.PSUS	96	3.10	1.10	-0.16	0.25	-1.19	0.49	5%	33%	14%	42%	6%
PTR.7.PSUS	96	3.30	0.95	-0.12	0.25	-0.83	0.49	1%	23%	29%	39%	8%
PTR.8.PSUS	96	2.85	0.96	-0.06	0.25	-0.69	0.49	7%	30%	34%	26%	2%
PTR_PSUS_avg	96	3.13	0.86	-0.16	0.25	-0.95	0.49	4%	28%	25%	38%	5%
PTR_avg	96	3.38	0.67	-0.08	0.25	-0.73	0.49	2%	21%	24%	43%	10%
PSI.1.SI	96	2.95	0.91	0.36	0.25	-1.15	0.49	0%	41%	27%	29%	3%
PSI.2.SI	96	3.24	0.89	-0.49	0.25	-0.72	0.49	2%	22%	28%	46%	2%
PSI_SI_avg	96	3.09	0.67	0.18	0.25	-0.36	0.49	1%	31%	28%	38%	3%
PSI.3.FC	96	2.70	0.96	0.21	0.25	-0.95	0.49	7%	43%	24%	25%	1%
PSI.4.FC	96	3.20	1.05	-0.02	0.25	-1.33	0.49	1%	35%	15%	41%	8%
PSI_FC_avg	96	2.95	0.91	0.16	0.25	-1.27	0.49	4%	39%	19%	33%	5%
PSI_avg	96	3.02	0.68	0.38	0.25	-0.46	0.49	3%	35%	23%	35%	4%
PPC.1.SE	96	3.16	0.97	-0.03	0.25	-1.14	0.49	1%	31%	24%	39%	5%
PPC.2.SE	96	3.21	1.00	-0.37	0.25	-1.03	0.49	3%	28%	18%	47%	4%
PPC_SE_avg	96	3.18	0.85	-0.28	0.25	-0.57	0.49	2%	30%	21%	43%	5%
PPC.3.PLOA	96	3.38	0.93	-0.34	0.25	-0.73	0.49	1%	21%	25%	46%	7%
PPC.4.PLOA	96	3.94	0.77	-0.33	0.25	-0.24	0.49	0%	3%	23%	51%	23%
PPC_PLOA_avg	96	3.66	0.77	-0.22	0.25	-0.68	0.49	1%	12%	24%	48%	15%
PPC_avg	96	3.42	0.77	-0.25	0.25	-0.72	0.49	1%	21%	22%	46%	10%
ATT1	96	3.72	0.83	-0.45	0.25	-0.19	0.49	0%	9%	24%	52%	15%
ATT2	96	3.85	0.87	-0.59	0.25	-0.13	0.49	0%	9%	18%	51%	22%
ATT3	96	3.69	0.84	-0.34	0.25	-0.34	0.49	0%	9%	27%	49%	15%
ATT4	96	3.64	0.77	0.03	0.25	-0.40	0.49	0%	5%	39%	44%	13%
ATT_avg	96	3.72	0.75	-0.28	0.25	-0.45	0.49	0%	8%	27%	49%	16%
BI1	96	3.60	0.89	-0.41	0.25	-0.53	0.49	0%	15%	23%	50%	13%
BI2	96	3.95	0.79	-0.57	0.25	0.21	0.49	0%	5%	18%	54%	23%
BI_avg	96	3.78	0.79	-0.43	0.25	-0.23	0.49		10%	20%	52%	18%

The concepts of Perceived Learning Orientation and Adaptability (PLOA) and Perceived Self-Efficacy (SE) define the latent variable, *Perceived Personal Competence (PPC)*. These dimensions reflect the participants' confidence in their abilities to use AI and their willingness to learn and adapt. Respondents demonstrated moderate level of self-efficacy (M=3.18, SD=0.85) and a positive learning orientation (M=3.66, SD=0.77) regarding the use of AI in accounting. As evidenced by "PPC.1.SE" (M=3.16) and "PPC.2.SE" (M=3.21), respectively, respondents feel relatively confident in their technical and problem-solving abilities and are appropriately prepared to work alongside AI, which is a good indicator for the adoption of AI in accounting. The willingness to embrace change and a positive attitude toward

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learning are evident in "PPC.4.PLOA" (M=3.94, SD=0.77), where 51% agree and 23% firmly agree that they explore and try new AI applications without hesitation. The response distribution was relatively symmetrical, with skewness and kurtosis values within the expected range.

Turning to *attitudes towards AI (ATT)*, accountants conveyed a fairly positive perspective (M=3.72, SD=0.75) towards AI integration in accounting. The standard deviation is relatively low, implying a fairly consistent viewpoints among respondents. The most positive attitude is observed in "ATT2" (M=3.85), where 51% agreed and 22% strongly agreed that using AI-powered accounting systems is interesting. Respondents expressed a positive belief that using AI in accounting is the best way to go (M=3.64). The distribution displayed slight negative skewness, indicating that more respondents provided higher ratings.

In terms of *behavioral intentions (BI*), respondents displayed a quite favorable inclination to use AI in the accounting field (M=3.78, SD=0.79). Participants in the study demonstrated a strong level of anticipation to use AI in the foreseeable future, as indicated by the high mean score of 3.95 (SD=0.79) in "BI2". Specifically, 54% agreed and 23% strongly agreed with the idea. Additionally, participants expressed a moderately strong willingness to use AI in their accounting work, as reflected in “BI1” (M=3.60). The results suggest a clear inclination and overall positive disposition toward adopting AI in their professional setting.

In terms of *actual usage of AI* in accounting, the survey results indicate that a relatively small percentage of accountants (18 out of 96) in the UAE are currently using AI technologies in their accounting work (18%), while 11 out of 96 participants (11%) are actively seeking training and certifications in AI applications to remain competitive in the industry. The findings further highlight despite growing awareness of the significance of AI in accounting, its actual integration into daily work practices is still relatively low, with only a few likely taking proactive steps to enhance their knowledge and competencies and meet future demands.

The above descriptive results provided insights into participants' adoption of AI in accounting. Despite variations in participants' perceptions evident from the skewness values, the survey outcomes highlighted a balanced perspective, where perceived benefits and opportunities in terms of productivity, skill development, collaboration, and career prospects were acknowledged alongside concerns about threats and risks. Respondents also exhibited a willingness to embrace AI's applicability and benefits, driven by a moderately positive attitude and intentions. In the end, there is a positive indication how findings align closely with the conceptual model in this study. This will be tested and discussed in the next sections.

Measurement model evaluation

Instrument reliability

Cronbach's alpha and composite reliability (CR) were tested to evaluate the internal consistency of the responses to the items within a measure, dimension, or construct in the model (Hajjar, 2018). Internal consistency measures the extent to which the items within a scale or questionnaire are correlated with each other. A Cronbach's alpha value of 0.6-0.7 is generally considered acceptable for reliability in exploratory research, while values of 0.7-0.9 indicates satisfactory to good reliability (Hair *et al.*, 2021).

Table 6: Internal Consistency Reliability

Key variable or Construct	Cronbach's Alpha	Composite Reliability
Perceived Benefits and Opportunities (PBO)	0.888	0.923
Perceived Threats and Risks (PTR)	0.865	0.889
Perceived Support and Influence (PSI)	0.670	0.766
Perceived Personal Competence (PPC)	0.851	0.855
Attitude (ATT)	0.924	0.729
Behavioral intention (BI)	0.866	0.672

Table 7 displays the reliability analysis of the scale used in the study. Each construct has appropriate Cronbach's alpha values ranging from 0.670 to 0.924, indicating acceptable and good internal consistency. The composite reliability also ranged from 0.672 to 0.923, exceeding the acceptable threshold of 0.6 (Hair *et al.*, 2021), signifying that the items within each construct are reliable and consistent in measuring the intended latent variable.

Correlation

Correlation analysis is a valuable tool for evaluating construct validity, aiding in the assessment of whether a construct behaves as expected based on theoretical or conceptual hypotheses. Strength and direction of relationships are indicated by correlation coefficients, ranging from -1 to 1 (Schepman and Rodway, 2020). **Table 8** presents the correlation between measurement variables, offering insights into potential patterns and associations that influence accountants' perceptions and intentions to adopt AI in the accounting.

Table 7: Correlation among Measurement Variables

		PBO	PTR	PSI	PPC	ATT	BI
PBO	**Pearson Correlation**	1	-0.175	.312**	.350**	.514**	.503**
	Sig. (2-tailed)		0.088	0.002	0.000	0.000	0.000
PTR	Pearson Correlation		1	-.314**	-.414**	-.647**	-.521**
	Sig. (2-tailed)			0.002	0.000	0.000	0.000
PSI	Pearson Correlation			1	.445**	.525**	.528**
	Sig. (2-tailed)				0.000	0.000	0.000
PPC	Pearson Correlation				1	.679**	.683**
	Sig. (2-tailed)					0.000	0.000
ATT	Pearson Correlation					1	.836**
	Sig. (2-tailed)						0.000
BI	Pearson Correlation						**1**
	Sig. (2-tailed)						

**. Correlation is significant at the 0.01 level (2-tailed).

Moderate to significant positive correlation were found between Perceived Benefits and Opportunity (PBO), Support and Influence (PSI), and Personal Competence (PPC) and Attitude (ATT), r=0.514**, 0.525**, and 0.679**, respectively. Likewise, a strong positive correlation (r=0.836**) exists between Attitude (ATT) and Behavioral Intention to Use (BI). This relationship suggests that one's intention to use AI in accounting is greatly influenced by their attitude. Moreover, this attitude is formed and reinforced by the benefits and opportunities linked to AI, the support and influence received from their social network, and their confidence in their abilities and aptitude to learn new technological skills.

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Conversely, there is a clear and significant negative correlation between Perceived Threats and Risks (PTR) and Attitude (ATT) (r=-0.647**), as well as between PTR and Behavioral Intention to Use (BI) (r=-0.521**). These findings suggest that if individuals perceive more threats and risks, their attitudes towards adopting AI in accounting may become less favorable. The correlation coefficients, marked with **, are statistically significant at the 0.01 level (2-tailed), suggesting strong correlations.

2.1.2 Hypothesis Testing

The study employed multiple regression analysis in SPSS to test the proposed eight relationships in the conceptual model. The results are presented in **Table 9.**

The initial phase of the analysis regressed the dependent variable (attitude towards using AI in accounting) on predictor variables PBO, PTR, PSI, and PPC. The analysis revealed a good model fit, indicated by the coefficient of determination R^2 = .721, where predictor variables explained 72.1% of the variance in attitude towards using AI in accounting. Additionally, results show a highly significant model summary, where independent variables significantly predict attitude towards using AI in accounting, F (4, 91) = 58.684, $p < .001$.

Furthermore, coefficients were examined to determine the impact of each factor on the criterion variable (attitude towards using AI in accounting). The findings indicate that perceived benefits and opportunities (PBO) has a significant positive effect on the accountants' attitude towards AI in accounting (β = 0.362, t = 4.545, $p < .001$). Thus, H_1 was supported, demonstrating that accountants are more favorable about integrating AI technology into their accounting work when they perceive more benefits and opportunities. The analysis also confirmed that perceived threats and risks (PTR) significantly and negatively influence the accountants' attitude towards AI in accounting (β = -0.452, t = -6.694, $p < .001$). The statistically significant negative coefficient supports the acceptance of $H_{2,}$ further implying that accountants are less inclined to adopt AI technology in their professional activities as perceived threats and risks increase.

Table 8: Hypothesis testing – Multiple regression

Hypothesis	Proposed Relationship	β	t	P-Value	Results
H_1	**PBO → ATT**	0.362	4.545	< .001	**Accepted**
H_2	**PTR → ATT**	-0.45	-6.59	< .001	**Accepted**
H_3	**PSI → ATT**	0.175	2.487	0.015	**Accepted**
H_5	**PPC → ATT**	0.336	5.119	< .001	**Accepted**
R^2	0.721				
F (4, 91)	58.864				

Note. *p < 0.05. PBO: Perceived benefits and opportunities; PTR: Perceived threats and risks; PSI: Perceived Support and Influence; PPC: Perceived Personal Competence; ATT: Attitude towards using AI in accounting

Hypothesis	Proposed Relationship	β	t	P-Value	Results
H_4	**PSI → BI**	0.116	1.551	0.124	**Rejected**
H_6	**PPC → BI**	0.204	2.661	0.009	**Accepted**
H_7	**ATT → BI**	0.685	8.289	< .001	**Accepted**
R^2	0.731				
F (3, 92)	83.185				

Note. *p < 0.05. PSI: Perceived Support and Influence; PPC: Perceived Personal Competence; ATT: Attitude towards using AI in accounting; BI: Behavioral intention to use AI in accounting

Hypothesis	Proposed Relationship	β	t	P-Value	Results
H_8	**BI → AU**	-0.15	-3.84	<.001	**Rejected**
R^2	0.136				
F (1, 94)	14.772				

Note. *p < 0.05. BI: Behavioral intention to use AI in accounting; AU: Actual use of AI in accounting

H_3 and H_5 hypothesize that perceived support and influence (PSI) and perceived personal competence (PPC), respectively, will positively influence the accountants' attitude towards AI in accounting. H_3 remains statistically significant (β = 0.175, t = 2,487, $p < .05$), supporting the hypothesis. H_5 was supported (β = 0.336, t = 5.119, $p < .001$), confirming a positive association between perceived support and influence and accountants' inclination to adopt AI technology in their professional activities, thus supporting the hypothesis.

The second stage of the analysis regressed the dependent variable (behavioral intention to use AI in accounting) on predicting variables of PSI, PPC, and ATT. The analysis revealed a highly significant model summary indicating independent variables significantly predicting behavioral intention to use AI in accounting, F (3, 92) = 83.185, $p < .001$. Moreover, the R^2 = .731 shows that the model explains 73.1% of the variability in behavioral intention to use AI in accounting. Hypothesis H_4 and $H_{6,}$ proposed that perceived support and influence (PSI) and perceived personal competence (PPC), respectively, would positively affect the accountants' attitude towards AI in accounting. H_4 was rejected due to lack of statistically significant effect on behavioral intention during multiple regression analysis. The study supports H_6 as perceived personal competence (PPC) is statistically significant (β = 0.204, t = 2.661, $p < 0.05$). The analysis confirms $H_{7,}$ showing that a positive attitude (β = 0.685, t = 8.289, $p < .001$) significantly and positively affects the accountants' intention to use AI in accounting. The accountants' growing acceptance of AI aligns with hypothesis H_7, suggesting their increasing inclination to integrate AI technology into their professional practices.

Table 9: Hypothesis testing – Binary logistic regression

		B	S.E.	Wald	df	Sig.	Exp(B)	Results
H_8	BI → AU1	-1.491	.475	9.848	1	.002	.225	**Rejected**
	Constant	7.459	2.018	13.667	1	0.000	1735.102	

Note: R^2 = .128 (Cox & Snell), .207 (Nagelkerke), Model χ^2=13.172, df = 1, $p < .001$

The linear regression analysis examining the relationship between behavioral intention and actual use in H_8 yielded a statistically significant model. However, the negative coefficient, which predicts a negative association contradicts our hypothesis, hence H_8 is rejected. Since actual usage in our data is dichotomous, a separate binary logistic regression was also performed to assess whether behavioral intention to use AI in accounting was associated with the likelihood of accountants actually using AI in accounting (AU1). **Table 9** shows that the Omnibus test for the dependent variable (AU1) reveals a statistically significant model, χ^2 (1, N = 96) = 13.172, p = < .001. The goodness-of-fit results adequately described the data and distinguished between those who will use AI in accounting or not. The model correctly classified 81.3% of the cases and explained between 12.8% (Cox & Snell R^2) and 20.7% (Nagelkerke R^2) of the dependent variable's variation. However, behavioral intention (BI) variable has a negative coefficient of -1.491 and an odds ratio of 0.225, indicating that a one-unit increase in behavioral intention decreases the likelihood of using AI in accounting by 0.225. This proves H_8 is rejected.

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Discussion of results

The results of this comprehensive study provided significant insights regarding the adoption of AI in accounting within the UAE context. The objectives were aimed at exploring perceptions among accountants and examining the effects on attitude and behavioral intentions.

The demographic information showcased the diverse composition of the participants and provided context for potential variations in survey responses. This was essential for understanding the how representative the sample was and how applicable our findings might be to a larger population. The sources of awareness and knowledge indicated that the influence of digital platforms and interpersonal networks through social media, online articles, conversations with colleagues, and professional bodies played significant roles in informing participants about AI in accounting and shaping perceptions. It is aligned with the research of Vărzaru (2022) that highlighted the importance of social influences and information dissemination channels.

This study gave insights on participants' perspectives regarding the usage, relevance, impact on employment and well-being, and future implications of AI in accounting. Participants demonstrated a generally positive attitude and inclination towards using AI in accounting. The optimism stems from acknowledging the perceived benefits and opportunities (PBO) of AI, where individuals recognize its value through practical effectiveness and relevance in their professional roles. The positive perception of AI aligns with the broader view that it can improve efficiency and job performance in accounting. It is also aligned with Peng and Hwang (2021), suggesting that creating a positive environment that emphasizes benefits can drive favorable attitudes and intentions. The impact of perceived benefits on attitude also resonates with the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory which highlights the importance of perceived usefulness in driving favorable attitudes (Cao et al., 2021). The results further emphasized a viewpoint on the future of accounting work, where collaboration between human accountants and AI systems will be required. Conversely, participants expressed concerns about perceived threats and risks (PTR) associated with AI adoption, including job polarization and the potential replacement of human accountants by AI. This is rather a balanced perspective, where accountants acknowledge the risks but does not view them as severe enough to cause anxiety or perceive oneself as highly vulnerable. The study highlighted the necessity of addressing these uncertainties through strategies that prioritize upskilling and adaptation. The findings indicated moderate perceived support and influence (PSI). Organizational support structures should be improved due to uncertainty regarding resource availability and technical assistance, despite the presence of peer influence. Respondents also exhibited moderate levels of personal competence (PPC). The accountants' confidence in their technical skills and openness to change is demonstrated by their willingness to collaborate with AI systems and their proactive approach to skill development and adaptation.

The correlation and regression analyses unveiled significant insights on the relationships between measurement variables. There was a strong connection between Attitude (ATT) and Behavioral Intention to Use (BI), indicating that a positive attitude greatly impacts the willingness to adopt AI in accounting. This supports the Theory of Reasoned Action (TRA) and the original Technology Acceptance Model (TAM), which suggest that individuals are more likely to engage in behaviors they perceive positively and have a favorable attitude towards (Dwivedi *et al.*, 2019). Correlations highlighted the interdependence of perceptions, attitudes, and intentions. PBO, PSI, and PPC are linked to positive attitudes, reinforcing the idea that these factors have significant influence on individuals' inclination and disposition towards AI adoption. Conversely, significant negative correlations between PTR and ATT, as well as PTR and PPC, demonstrated how higher perceived threats and risks were linked to less favorable attitudes and lower personal competence, potentially hindering the adoption of AI.

However, the transition from intention to actual use of AI in accounting presented intricacy. The study revealed lack of practical implementation of AI, despite positive intentions. Behavioral Intention (BI) did not directly predict actual usage. Only a minority of accountants use AI technologies, with some actively pursuing training and certifications. This identifies potential barriers to implementing AI and emphasize the need for better organizational support structures to bridge the gap between intention and action, facilitating a smoother transition toward AI-driven accounting practices.

2.2 Practical implications and contributions

The research presented in this study contributes to the broader understanding of technology acceptance and avoidance models. Furthermore, it enhances the existing literature through:

1. *Conceptual development of a comprehensive and balanced framework*: While many studies focus on standalone acceptance or avoidance concept of AI adoption, this study offered empirical data to the development of a more comprehensive and balanced theoretical model for AI acceptance and avoidance, in general. The proposed Integrated AI acceptance-avoidance model (IAAAM) proposed is a complete concept that addresses both benefits and risks, tackles appropriate factors influencing acceptance, along with the interdependence of attitudes, intentions, and perceptions regarding AI use in accounting. The model can be employed in the development of organizational interventions aimed at maximizing benefits and mitigating risks on AI adoption.
2. *Model Validation and Extension:* The study validated a conceptual model that explains the adoption of AI in accounting. It emphasized the significance of selected variables in shaping attitudes and intentions and extended the concept that attitude plays a crucial role in determining

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behavioral intentions. It also introduced perceived personal competence as an important factor in understanding and predicting attitudes and intentions towards using AI.

The study not only provides valuable insights into the perceptions of accountants towards AI adoption in accounting within the UAE context but also provides several practical implications:

1. *Supporting positive attitudes through training and education* - The strong inclination among accountants to gain more knowledge about AI implies a compelling demand for educational programs and training opportunities in AI for accountants. Organizations, educational institutions, professional bodies can provide training and resources to enhance skills and increase confidence, thereby promoting a more receptive environment for AI integration.
2. *Addressing concerns and risk*: AI concerns and risks negatively impact perceptions. Organizations should address accountants' concerns about job displacement and skill requirements by implementing strategies that acknowledge the balanced perceptions of benefits and risks. Proactive upskilling and reskilling measures can alleviate concerns and equip employees for the changing landscape.
3. *Recognizing Social Influence*: The influence of peers and colleagues on the formation of attitudes and intents emphasize the need for organizations, educational institutions, professional bodies in fostering a culture that values AI literacy and encourages knowledge sharing among peers.
4. *Favorable facilitating conditions and support for AI adoption*: The disparity between intention and actual use emphasizes how crucial it is for companies to ensure the presence of essential infrastructures and enabling technologies. To foster AI learning and application, adequate training, technical support, and a supportive workplace culture is important.

CONCLUSION& RECOMMENDATIONS

Artificial intelligence is accelerating the transformation of accounting processes and operations., but despite the apparent opportunities and advantages, the workforce directly affected by these changes face the main challenge. This research addresses the lack of research on the perceptions and attitudes of accountants in UAE regarding the adoption of AI in the field of accounting and provided a conceptual framework to understand how these perceptions may impact their attitudes and usage behavior. True enough, the significance of the study lies in its contribution to a better understanding of AI adoption among accountants through the development of a new integrated AI acceptance-avoidance model (IAAAM), which offered a complete paradigm addressing both benefits and risks as appropriate factors influencing AI acceptance, as well as the interdependence of perceptions, attitudes, and intentions regarding AI use in accounting. The findings provided empirical evidence on accountants' perceptions, attitudes, and willingness to adopt AI, contributing to the existing literature. The existence of a gap between intention and actual usage, despite positive attitudes and intentions, emphasized the need for support mechanisms and skill development opportunities. This research advances academic knowledge and offers practical guidance to policymakers, academic institutions, professional bodies, and organizations in the UAE in shaping the future of accounting in an AI-driven landscape.

Limitations and future research

The study has several limitations but provides foundation for future research on AI adoption in the accounting profession. First, the research's non-probability sampling method using convenience and snowball techniques, may have introduced bias and limit representativeness. It is recommended to adopt a more comprehensive and diverse sampling method that includes a wider range of accountants from various backgrounds and industries in the UAE. Comparative study between nationalities is suggested to understand any cultural and contextual aspects impacting the AI adoption in accounting. Second, the study did not investigate how demographic factors affect perception and adoption. Additional research is needed to enhance the proposed model. Third, confirmatory factor analysis, path analysis, and structural equation modeling can further examine multiple complex conditions and relationships in the model, complementing the use of SPSS correlation and regression for hypothesis testing. Lastly, further study to explore the barriers to the practical implementation of AI in the accounting profession would be relevant to aid in the development of effective strategies for AI integration.

3. APPENDIX

Appendix A: Variable definitions

Key variable or construct	Working definition	References
Attitude (ATT)	The accountant’s positive or negative feelings and disposition about using AI in accounting	(Davis, Bagozzi, and Warshaw, 1989) (Fayad and Paper, 2015) (Dwivedi *et al.*, 2019)
Behavioral Intention (BI)	The measure of strength of one’s intention to perform a	(Dwivedi *et al.*, 2019)

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	specific behavior	
Perceived Support and Influence (PSI)	The extent to which accountants perceive that the necessary resources, support, and infrastructure are available to facilitate the use of AI (*facilitating conditions)* and that there is enough pressure or influence from significant others to engage in the use of AI *(social influence)*	(Venkatesh *et al.*, 2003)
Perceived Benefits and Opportunities (PBO)	The extent to which accountants perceive substantial rewards for using AI that comes in the form of performance improvement and productivity *(performance expectancy or perceived usefulness),* the simplicity and convenience to use the AI technology *(effort expectancy or perceived ease of use),* and the potential advantages, positive outcomes and growth opportunities that may arise from using AI *(perceived opportunity).*	(Venkatesh *et al.*, 2003) (Maclnnis and Jaworski, 1989)
Perceived Threats and Risks	The accountants' perception and subjective assessment of the potential negative consequences or uncertainties associated with AI adoption in accounting like employment and well-being outcomes, privacy, security, financial risks, and the potential for negative impact on work or personal life *(perceived severity)* and the likelihood of personally experiencing the AI-related threat and risk *(perceived susceptibility)*	(Liang and Xue, 2009) (Carpenter *et al.*, 2019a)
Perceived Personal Competence	The extent to which accountants perceive their ability and confidence to successfully use AI technologies which includes technical skills, familiarity with technology, and problem-solving capacities *(self-efficacy),* and the extent to which they are interested to learn and upskill, innovate, and adapt to the changes brought by AI *(perceived learning orientation and adaptability)*	(Parasuraman and Colby, 2015)

Appendix 2: Survey questions for each construct and item indicator

Key variable or Construct	**Acronym**	**Indicator (From 1 – strongly disagree to 5 – strongly agree)**	**Reference**	**Count**
Perceived Benefits and Opportunities (PBO)	PBO-1-PE	Using AI in Accounting will increase my productivity and overall job performance.	(Venkatesh, Thong, and Xu, 2012; Dwivedi *et al.*, 2017)	1
	PBO-2-PE	I believe that implementing AI in Accounting will relieve accountants from routine tasks and manual workload, enabling them to focus on higher-level value-added tasks like strategic financial analysis and decision-making.	(Venkatesh, Thong, and Xu, 2012; Dwivedi *et al.*, 2017)	2
	PBO-3-PE	I believe that AI has useful applications in accounting and should be integrated into the accounting profession.	(Venkatesh, Thong, and Xu, 2012; Dwivedi *et al.*, 2017)	3
	PBO-4-EE	I find AI easy to use in the accounting function.	Venkatesh, Thong and Xu, 2012; Dwivedi *et al.*, 2017)	4
	PBO-5-EE	I think AI will be flexible to use and interact with if implemented in my accounting work.	(Davis, Bagozzi, and Warshaw, 1989; Dwivedi *et al.*, 2017)	5

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	PBO-6-O	I think AI will generate more employment opportunities in the accounting sector.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	6
	PBO-7-O	I believe the future of accounting work will require collaboration between human accountant and AI.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	7
	PBO-8-O	The use of AI in accounting promotes the development of new skillsets and competencies.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	8
	PBO-9-O	If I use AI, I will have the opportunity to enhance my job engagement and future career prospects.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	9
	PBO-10-O	I think that integrating AI technologies into accounting can improve work-life balance and overall well-being among accountants, eventually.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	10
Perceived Threats and Risks (PTR)	PTR-1-PSEV	I think it is unsafe to use AI in accounting because of privacy, trust, and security concerns that can compromise confidentiality and integrity of financial systems and information.	(Liang and Xue, 2009; Dwivedi *et al.*, 2017)	11
	PTR-2-PSEV	Systemic biases, algorithmic flaws, and system malfunctions innate to AI can lead to erroneous financial analyses and bad business decisions.	(Liang and Xue, 2009; Dwivedi *et al.*, 2017)	12
	PTR-3-PSEV	In my view, AI will replace human accountants in the foreseeable future, leading to unemployment or reduced job opportunities in the accounting field.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	13
	PTR-4-PSEV	I think job polarization is highly likely, with specialized AI-related accounting roles becoming more prevalent while traditional accounting roles declining in demand.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	14
	PTR-5-PSUS	I feel stressed on the fact that I need to constantly upskill and reskill to adapt to AI-driven changes in accounting.	(Liang and Xue, 2009; Chen and Zahedi, 2016)	15
	PTR-6-PSUS	I am worried AI will replace me in my job.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	16
	PTR-7-PSUS	I am anxious that using AI in the field of accounting could significantly reduce work opportunities, making it harder to plan my future career.	(Brougham and Haar, 2018; Brougham, Haar and Tootell, 2019)	17
	PTR-8-PSUS	The extent of my worry about AI's threats and risks affecting me is high.	(Cao *et al.*, 2021)	18
Perceived Support and Influence (PSI)	PSI-1-SI	My peers, superiors, business partners, and other people who influence my behavior think that I should use AI in Accounting.	(Venkatesh, Thong and Xu, 2012; Zuiderwijk, Janssen and Dwivedi, 2015; Dwivedi *et al.*, 2017; Cao *et al.*, 2021)	19

	PSI-2-SI	I use AI applications because of the proportion of coworkers who use it.	(Jen, Lu, and Liu, 2009)	20
	PSI-3-FC	I have available and accessible resources, technical assistance, support, and training necessary in the use of AI in Accounting.	(Jen, Lu and Liu, 2009; Venkatesh, Thong and Xu, 2012; Cao *et al.*, 2021)	21
	PSI-4-FC	In my view, my organization and the senior management would support the use of AI in Accounting, in general.	(Dwivedi *et al.*, 2017)	22
Perceived Personal Competence (PPC)	PPC-1-SE	I can use AI technologies without aid because I am confident in my technical and problem-solving skills and knowledge.	(Parasuraman and Colby, 2015)	23
	PPC-2-SE	I am adequately prepared to work alongside Artificial Intelligence.	(Parasuraman and Colby, 2015)	24
	PPC-3-PLOA	Learning and becoming skillful at using AI in my accounting work is easy for me.	(Parasuraman and Colby, 2015)	25
	PPC-4-PLOA	I do not hesitate to explore and try new AI applications in order to adapt to the changes in accounting.	(Parasuraman and Colby, 2015)	26
Attitude (ATT)	ATT1	I like the idea of using and working with AI in Accounting.	(Jen, Lu, and Liu, 2009; Dwivedi *et al.*, 2017; Cao *et al.*, 2021)	27
	ATT2	Learning and using AI-powered accounting system is interesting to me.	(Jen, Lu, and Liu, 2009)	28
	ATT3	I am excited about the changes that AI will bring to the accounting profession.	(Dwivedi *et al.*, 2017)	29
	ATT4	Overall, I think using AI in accounting is the best way to go.	(Mensah, Zeng and Luo, 2020)	30
Behavioral Intention (BI)	BI1	I plan and intend to use AI in my accounting work.	(Venkatesh, Thong and Xu, 2012)	31
	BI2	I predict that I will use AI in Accounting in the foreseeable future.	(Venkatesh, Thong and Xu, 2012)	32
Actual use behavior (AU)	AU1	I currently use (or have used) AI technologies in my accounting work and function.	User-initiated	33
	AU2	I am obtaining training and certifications in AI applications necessary to perform my accounting function or to upgrade myself and stay competitive in the industry.	User-initiated	34

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