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AI Adoption in Accounting: Insights From a French Professional Services Context

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ABSTRACT

Artificial Intelligence (AI) is reshaping accounting services, making it vital to understand the factors that drive its adoption. This study investigates AI adoption among French accounting professionals using an integrated Technology Acceptance Model (TAM) and Technological-Organizational-Environmental (TOE) framework. A cross-sectional survey of 238 accounting professionals was analyzed using structural equation modeling (SEM). The results show that perceived compatibility, IT infrastructure, financial readiness, trust, and vendor support positively influence adoption intention through their effects on perceived usefulness and ease of use, while perceived cost acts as a significant barrier. This model explains a substantial portion of the variance in adoption intention. The study offers practical recommendations for firms and AI vendors and contributes crucial empirical evidence on AI acceptance within the French professional service context.

KEYWORDS

Artificial Intelligence, Accounting, Technology Adoption Model, France

INTRODUCTION

Artificial intelligence (AI) is evolving rapidly, driving significant changes in various sectors and reshaping established processes and decision making. In professional services industries such as accounting, the ability of AI to automate complex and knowledge-intensive tasks that have traditionally required human expertise is particularly promising (Spring et al., 2022). This technological advance allows accountants to focus on more strategic and analytical activities rather than routine data management, improving the overall quality of decision making (Madakam et al., 2019; Mendling et al., 2018).

Despite these potential benefits, the integration of AI in professional services presents considerable challenges (Chavali et al., 2024; Yang et al., 2024). Studies have shown a high rate of failure for AI initiatives, often due to its disruptive nature, difficulties in workflow alignment, significant financial

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costs, and perceived risks (Johnson et al., 2022; Osoba and Welser 2017; Vial et al., 2023). This process is further complicated by a critical organizational paradox: On the one hand, firms face a shortage of skilled professionals, but on the other hand, the existing workforce resists AI adoption because they are often anxious about job security and unprepared for new technologies (Simon and Everaert, 2021). Resolving this paradox is not a technological problem but an organizational one, demanding substantial investment in targeted reskilling, proactive change management, and the development of supporting infrastructure. These combined factors demonstrate that understanding the role of organizational capabilities is central to navigating the complex dynamics of AI adoption in professional services.

Although the adoption of AI has been explored in various professional sectors including actuarial practice, health care, banking, financial and legal services (Rahman et al., 2023), the accounting profession has received relatively less scientific attention (Yang et al., 2024; Saci, 2021). Past studies in these other areas have identified influencing factors such as the organizational availability of AI, data confidentiality concerns, and perceived usefulness (PU; Rahman et al., 2023). Similarly, important research has focused on the integration of AI in broader contexts such as government, manufacturing, small and medium-sized enterprises, and agritech (Chatterjee et al., 2021; Issa et al., 2022; Polisetty et al., 2024). However, because of the particular operational complexities, knowledge-intensive nature, and unique regulatory requirements of professional service fields, information from these broader contexts does not necessarily translate directly into them (Maragno et al., 2023; Yang et al., 2024). Given the challenges and opportunities associated with adopting AI, this study aims to explore the following research question: *What factors specifically influence AI adoption intentions in accounting firms?*

The theoretical foundation of this study lies in a framework integrating the technology acceptance model (TAM) with the technology–organization–environment (TOE) framework (Abdou & Jasimuddin, 2020; Almuraqab et al., 2021). This integration posits that external TOE factors, encompassing technological characteristics, organizational readiness, and environmental influences, affect adoption intention indirectly through the mediating roles of the TAM constructs: PU and perceived ease of use (PEOU). The TOE framework offers a comprehensive view of the contextual determinants of AI adoption (Tornatzky & Fleischer, 1990), whereas TAM captures the individual cognitive evaluations that directly shape behavioral intention (Chatterjee, 2021; Yousafzai et al., 2007). Applying this integrated model, this study examines AI adoption within French accounting firms by focusing on applications with a direct impact on professional practice, such as the automation of routine tasks, real-time data analysis, and the strengthening of strategic advisory roles.

The French accounting industry is navigating two major technological shifts. First, advances in cloud technology and AI are driving automation and efficiency in data processing (Frey & Osborne, 2017). Second, the sector is undergoing a legally induced digitalization, with government mandates increasingly requiring the dematerialization of tax declarations and invoices, culminating in mandatory e-invoicing between all businesses by 2027. These regulatory pressures have compelled accounting professionals to evolve their operating models to manage dematerialized client workflows, making the study of AI adoption particularly timely and critical in this context (Azzam et al., 2023).

The study is based on a quantitative research model using a structured questionnaire distributed to professionals in French accounting firms. Data were analyzed using structural equation modeling (SEM) to evaluate measurement and structure models. The model was validated for reliability and validity using established statistical techniques, including confirmatory factor analysis, composite reliability, and average variance extracted (AVE). The findings of this study indicate that usability and usefulness are key factors—e.g., compatibility, information technology (IT) infrastructure, financial readiness (FR), confidence, competitive advantage (COA) and vendor support (VS)—that influence AI adoption.

This study responds to limited empirical research on technology adoption in the accounting field (Jackson and Allen, 2024a; Moll and Yigitbasioglu, 2019; Norzelan et al., 2024) by exploring key

drivers and barriers through the application of an integrated TAM–TOE framework in the accounting context. For managers, our study highlights the need to align AI tools with existing processes, invest in training and infrastructure, build trust, and work closely with suppliers. AI providers should focus on user-friendly and cost-effective solutions and demonstrate their value in overcoming cost concerns by providing a roadmap for successful integration of AI into accounting. The study thus provides an operational framework to support the effective integration of AI into the accounting sector.

The remainder of this paper is structured as follows: The following section reviews the theoretical background and develops the hypotheses. Next, the research methodology is detailed. The subsequent two sections present the results and discuss the findings, and the final section concludes with key insights and directions for future research.

THEORETICAL BACKGROUND

Artificial Intelligence in the Accounting Field

AI has been defined in accounting literature through various lenses. AI refers to the “intelligence exhibited by software or machinery that replicates human cognitive functions” (Fisher et al., 2016, p. 157). Kaplan and Haenlein (2019) and Agustí and Orta-Pérez (2023) extended this view, emphasizing AI's ability to interpret external data, learn from it, and apply this learning adaptively to fulfill specific tasks. While AI's scope can encompass theoretical advances in computing systems (Petkov, 2020), this study adopts a practical definition, considering AI as “a computer program or software application capable of mimicking or replicating human behavior” (Ng and Alarcon, 2020, p. 1).

Some definitions underline several sub-domains of AI relevant to accounting: machine reasoning, machine learning (ML) and natural language processing. Early AI applications, such as expert systems, illustrate machine reasoning and simulate coded knowledge-based decision making. ML uses algorithms to detect patterns and make predictions from large data sets, while natural language processing allows machines to interact with users through human language (Ng and Alarcon, 2021).

In the accounting field, AI is recognized for its transformative potential, particularly with regard to improving operational efficiency, data accuracy, and the strategic value of accounting work. One of AI's main features is the automation of repetitive and time-consuming tasks, such as data entry, transaction classification, and reconciliation, which have traditionally been performed manually and are often prone to errors (Yathiraju, 2022). Automation in these areas not only increases productivity but also allows accountants to focus on higher-level tasks, including financial analysis, forecasting, and strategic advisory roles. AI-driven algorithms also increase the accuracy of financial data classification and improve the reliability of financial reporting (Yathiraju, 2022; Rong et al., 2024).

AI also supports decision making through predictive analytics by analyzing historical financial data to discover trends and expected outcomes, facilitating proactive planning in areas such as budgeting and investment (Cubric, 2020). These capabilities are based on two fundamental technological foundations: expert systems, which simulate human reasoning through coded domain knowledge, and ML, which allows systems to self-improve by learning from past data (Chen, 2019; Norzellan et al., 2024).

In particular, tools such as document recognition software, automated data entry systems, and generative AI for financial analysis are now widely integrated into the daily workflows of accounting firms, particularly in France (Bastuck, 2023). With the implementation of mandatory electronic invoicing by 2027, AI is poised to further reduce manual intervention in value added tax (VAT) returns, payment tracking, and reconciliation processes, potentially replacing a significant portion of traditional accounting services.

These changes highlight a broader transformation of the role of accountants from performing routine operational tasks to being data-driven strategic advisors. However, the adoption of AI also presents challenges. A growing skill gap in technology literacy limits the ability of the profession to take full advantage of AI (Howieson, 2003), requiring investment in skills improvement and

continuing training. Ethical issues such as data confidentiality, algorithmic bias, and transparency also demand special attention, requiring strong governance frameworks to ensure responsible adoption (Madakam et al., 2019; Mendling et al., 2018). Ultimately, AI is an integral part of accounting's digital transformation. By automating routine tasks and enabling predictive analysis, it not only streamlines operations but fundamentally redefines the accountant's role as a strategic advisor in a data-driven economy.

Technology Adoption Models

This research considers two models for technology adoption: the TOE model and the TAM framework, both of which are commonly used in organizational studies (Henaó-Ramírez and Lopez-Zapata, 2022; Norzelan et al., 2024; Yang et al., 2024). Numerous empirical and conceptual studies have highlighted the significant, predominant, and pertinent role of the TAM model and the TOE framework in independently explaining technology adoption, though each model has its own limitations.

The TAM Framework

The TAM, rooted in the theory of reasoned action and the theory of planned behavior (Ajzen, 1985), is a used framework for understanding technology adoption (Almuraqab et al., 2017; Gao and Bai, 2014; Jasimuddin et al., 2017). The TAM identifies two particular beliefs that shape a person's attitude toward using a system, each determining intention to use the system and actual use. The first is PU, which refers to the extent to which a person believes that a specific system will improve their performance at work. If employees see the benefits of new technology in increasing their productivity and efficiency, they are more likely to adopt it. The second belief is usability, defined as the extent to which a person believes that using a system will require minimal effort (Davis, 1989). These two factors consistently account for a large share (about 40%) of technology adoption (Autry et al., 2010). However, the precise definitions of variables in extended TAM models remain somewhat ambiguous (Henaó Ramirez and Lopez-Zapata 2022). Perceived ease of use and PU are recognized in global accounting research as key drivers of intent and readiness to adopt emerging technologies.

The TOE Framework

Originally introduced by Tornatzky et al. (1990), the TOE framework classifies the various elements influencing technology adoption into three main dimensions: technological, organizational, and environmental. Despite its structure, the TOE framework is frequently regarded as a flexible and non-prescriptive model (Zhu and Kraemer, 2005) and one that allows researchers to incorporate a wide range of influencing factors (Baker, 2012). Its adaptability is further evidenced by the diversity of variables explored in more recent studies (Maragno et al., 2023; Neumann et al., 2022). This feature makes the framework particularly suitable for structured yet open-ended investigation. In the context of this study examining drivers of AI adoption in professional service firms, the TOE framework proves highly applicable, as it accommodates the technological complexity of AI, internal organizational factors, and external environmental influences (Yang et al., 2024). This framework offers a holistic picture of technology adoption by users, encompassing its implementation process and anticipated challenges (Gangwar et al., 2015).

An Integrated TAM–TOE Model for AI Adoption

This study proposes and empirically examines an integrated TAM–TOE framework to provide a more comprehensive, context-sensitive approach to understanding AI adoption in professional services, such as accounting. Integrated models in technology adoption combine elements from various theoretical frameworks to offer a more complete view of the factors affecting the acceptance and use of new technologies. This synthesis enables researchers to consider a wider array of variables and viewpoints in their investigations (Wamba and Queiroz, 2022).

Independently, the TAM and the TOE framework have been widely validated in technology adoption research, each addressing distinct dimensions of adoption (Oliveira and Martins, 2011; Vasarhelyi et al., 2012). The TAM is particularly effective at capturing individual-level acceptance behaviors by focusing on personal motivations, specifically PU and PEOU (Neumann et al., 2022). Numerous studies consistently highlight these factors' positive impact on technology acceptance within the accounting field. This body of research covers various innovations, including data visualization (Buchheit et al., 2020), cloud computing (Le and Cao, 2020; Tarmidi et al., 2014), blockchain (Cazazian, 2022), accounting information systems (Qader et al., 2022), AI (Damerji and Salimi, 2021), and technology (Jackson and Allen, 2024a).

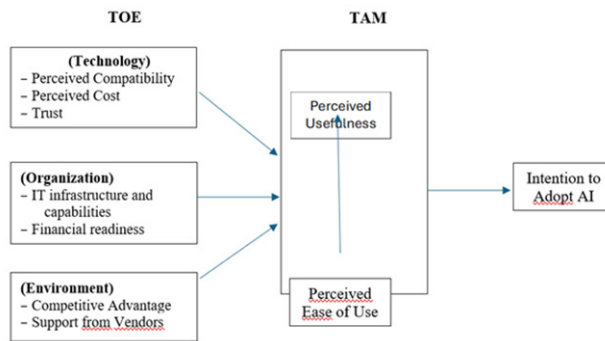
In contrast to TAM, TOE views technology adoption from an organizational perspective (Neumann et al., 2022). It suggests that the process of adopting new technologies is shaped by an organization's technological, organizational, and environmental conditions (Baker, 2012). However, it does not identify specific influencing variables (AboelImaged, 2014; Neumann et al., 2022). As a result, researchers must identify context-specific factors on the basis of prior literature and relevant theoretical foundations, recognizing that "different types of innovations have different factors that influence their adoption" (Baker, 2012, p. 236). This framework's inherent flexibility allows researchers to identify context-specific and novel determinants relevant to emerging technologies like AI (Yang et al., 2024). The TOE framework has been applied in accounting and auditing research. Jackson and Allen (2024b) found that leadership, innovation strategy, skilled staff, and organizational readiness enable adoption, while resistance to change, limitations in expertise, and cost-related concerns act as barriers. Yang et al. (2024) identified six factors for AI adoption in audit firms, including technological capabilities, innovation readiness, competitive pressure, and regulatory factors. However, the overall perspective of the TOE does not explicitly consider individual attitudes or psychological factors that influence technology adoption.

The integration of the TAM and TOE frameworks thus leverages their complementary strengths, offering a more holistic perspective that simultaneously considers individual perceptions and broader organizational and environmental realities. According to Kamble et al. (2021), the integration of the TOE model with the TAM may be more effective for studying behavioral intentions. This integrated model is particularly useful for examining the adoption of AI in professional services, where successful implementation depends on both individual user acceptance and strategic alignment within organizational contexts. Previous studies that merged these frameworks to examine technologies such as cloud computing and enterprise resource planning have highlighted the benefits of such an integrated approach (Gangwar et al., 2015). Specifically, the combined TAM–TOE model uniquely facilitates analysis of interactions between individual adoption behaviors and organizational strategies, recognizing that the adoption of AI generally involves collaborative organizational change rather than individual efforts. Therefore, this integrated approach not only captures the established factors influencing technology acceptance but also examines the unexplored organizational and environmental influences that are critical to successful adoption and implementation of AI in professional services companies.

Proposed Conceptual Model and Hypotheses Formulation

The model proposed and tested in this research is illustrated in Figure 1.

Figure 1. Theoretical Framework of the Study



Note. TOE = technological–organizational–environmental framework; TAM = technology acceptance model; IT = information technology; AI = artificial intelligence.

This framework integrates three key drivers of AI adoption: technological, organizational, and environmental factors. In technology, variables such as perceived compatibility (PCM; Masood and Egger, 2019; Wamba and Queiroz, 2022), perceived cost (PCS; Teo et al., 2009) and trust (Alazab et al., 2021; Chittipaka et al., 2023; Jackson and Allen, 2024b) are commonly identified as influential. At the organizational level, elements such as IT infrastructure (Chittipaka et al., 2023; Jackson and Allen, 2024a; Pillai et al., 2022; Wei et al., 2015; Yang et al., 2024) and FR (Henao Ramirez & Lopez-Zapata, 2022; Jackson and Allen, 2024a; Lai et al., 2018; Yang et al., 2024) serve as key facilitators. From an environmental perspective, factors such as COA (Chatterjee et al., 2021) and VS (Ghobakhloo and Tang, 2013; Pillai et al., 2022) are recognized for their role in shaping adoption outcomes. In addition, the framework is inspired by the TAM, which incorporates PEOU and PU as essential technological constructs influencing technology adoption.

Technological Factors

PCM refers to the extent to which an innovation aligns with users’ existing values, past experiences, and operational needs (Almuraqab & Jasimuddin, 2017; Géczy et al., 2012). Within organizations, compatibility is not only a technological consideration but also a reflection of internal structures, behavioral standards, and ingrained processes (Peng et al., 2012). Essentially, it reflects how a new technology such as AI can be seamlessly integrated into an organization’s current systems and infrastructure (Géczy et al., 2012). A major challenge in adopting AI is the potential gap between innovation and existing systems. Old accounting systems are often obstacles to technological progress because of their incompatibility with new tools (Merhi and Harfouche, 2022). This misalignment can result in significant costs and delays as organizations attempt to modify or replace obsolete systems. Moreover, resistance to change is a common barrier to technology adoption (Premkumar and Roberts, 1999). When a new system is perceived to be incompatible, it can affect its usability and usefulness, two key factors that influence user acceptance (Chatterjee et al., 2021; Gangwar et al., 2015). On the basis of these arguments, we propose the following hypotheses:

H1a: Perceived compatibility has a positive impact on perceived usefulness.

H1b: Perceived compatibility has a positive impact on perceived ease of use.

PCS issues are understood as barriers and negatively influence the adoption of innovative technology (Maduku et al., 2016; Paul et al. 2021; Reyes et al., 2016). Implementing new IT systems often involves substantial initial investment in software or online services (Ghobakhloo & Tang,

2013), plus additional costs associated with planning, implementation, and training. This challenge may lead organizations to perceive the cost of new technologies such as AI as prohibitive and thus to discourage investment (Ghobakhloo & Tang, 2013). High costs and uncertain returns limit appreciation of its strategic benefits, thus reducing its PU. In addition, costly or complex implementation can make AI more difficult to use even if the system is designed to be user-friendly. This perception is exacerbated in firms without technical expertise, as they may need to spend more on external consultants or training, further increasing the perceived difficulty. This reasoning supports the following hypotheses:

- H2a: Perceived cost negatively influences perceived usefulness.
H2b: Perceived cost negatively influences perceived ease of use.

Trust in technology (TR) reflects users' confidence in a technology's capabilities and supporting infrastructure (McKnight et al., 2011). Uncertainty regarding system performance, particularly security and privacy, can undermine TR (Chatterjee et al., 2021). TR is key to mitigating this uncertainty (Yang et al., 2019), particularly for emerging technologies where information is limited. A pre-existing feeling of trust toward a specific technology can reduce uncertainty and enhance PU (Gefen et al., 2003; Schaupp & Carter, 2010). Recent research has indicated that trust is critical in assuring the acceptance, continued advancement, and development of AI (Akakpo et al., 2025; Almuraqab et al. 2024; Maldonado-Canca et al., 2024). Users' belief in a system's reliability and integrity directly influences their perception of its usefulness, leading to increased confidence and a belief in improved job performance (Chatterjee et al., 2021; Susanto & Goodwin, 2011). These observations supports the following hypothesis:

- H3. Trust has a positive impact on perceived usefulness.

Organizational Factors

IT infrastructure and capabilities (IF) include both the tangible and the intangible resources (Iacovou et al., 1995) that an organization utilizes for the implementation of IT innovations. Tangible resources include technological elements such as servers, middleware, storage, hardware, and networking, while intangible resources focus on knowledge assets, human resources work concerning IT, and managerial skills. These resources have a significant impact on AI adoption (Merhi and Harfouche, 2023), as demonstrated by research linking IT infrastructure to Radio Frequency Identification (RFID) uptake (Wei et al., 2015); this connection highlights the role of IF in obtaining COA (Bharadwaj, 2000). Key elements of AI preparation are data storage, networking, and scalable computing (Jöhnk et al., 2021). A robust IT infrastructure is essential for successful adoption of AI (Rong et al., 2024) as its absence can create significant barriers. If an organization has the infrastructure and expertise to support them, employees are more likely to adopt new technologies and recognize their usefulness. The above discussion leads to the following hypotheses:

- H4a: IT infrastructure has a positive impact on perceived usefulness.
H4b: IT infrastructure has a positive impact on perceived ease of use.

FR, which includes the availability of funds for implementation, infrastructure, training, and support, is a critical enabler of successful technology adoption (Henao-Ramírez & López-Zapata, 2022; Kamble et al., 2021). Organizations with adequate financial resources can invest in advanced, reliable technologies and skilled personnel, facilitating smoother integration and minimizing disruptions (Maduku et al., 2016). This financial capacity also supports training and change management efforts, which are essential for employee engagement and understanding. In contrast, insufficient

investment can hinder the effective use of innovations like AI, reducing their PU. When employees are equipped with the right tools and support, they are more likely to recognize the practical value of new technologies, leading to the hypothesis that FR positively influences PU (Ifinedo, 2011; Oliveira and Martins, 2011; Yee-Loong Chong and Ooi, 2008). This discussion leads to the development of the following hypotheses:

H5: Financial readiness has a positive impact on perceived usefulness.

Environmental Factors

COA describes the extent to which a technological factor offers a benefit for organizations (Rogers, 2003). AI's potential to drive innovation and create new opportunities makes its adoption a key factor in achieving COA (Andrews, 2017; Fast and Horvitz, 2017). AI's ability to automate complex decision making and problem solving tasks, previously reliant on human cognitive capabilities provides significant advantages (Choudhury et al., 2020). AI-based systems often surpass human capabilities in areas such as medical diagnosis, candidate selection, product design, and investment analysis (Verganti et al., 2020). This automation contributes to COA (Curran & Purcell, 2017), fostering employee satisfaction and potentially enhancing perceptions of usefulness and ease of use (Chatterjee et al., 2021). This observation leads to the following hypotheses:

H6a: Competitive advantage has a positive impact on perceived usefulness.

H6b: Competitive advantage has a positive impact on perceived ease of use.

Support from vendors (SV) encompasses the marketing activities associated with innovative technology as well as the training and assistance provided by technology suppliers (Maduku et al., 2016). Research has highlighted the crucial role of SV in technology adoption and implementation (Maduku et al., 2016; Pillai et al., 2022). As a complex and emerging technology, AI presents challenges for accounting professionals who often lack the expertise to utilize it effectively in their daily tasks. Consequently, SV is anticipated during the adoption phase (Albert, 2019). The enhancement of knowledge among accounting professionals, facilitated by their own efforts and contributions from organizational partners, can facilitate AI adoption by enhancing professionals' understanding of AI's usefulness and ease of use (Hottenrott and Lopes-Bento, 2016). This observation leads to the following hypotheses:

H7a: Support from vendors positively influences perceived usefulness.

H7b: Support from vendors positively influences on perceived ease of use.

PU and PEOU

In the TAM, intention to use reflects the likelihood of technology adoption (Zhang et al., 2023). PU and PEOU are key predictors of technology acceptance, explaining up to 40% of behavioral intention variance (Almuraqab & Jasimuddin, 2016; Aubert et al., 2012; Venkatesh, 2000). PEOU represents the degree to which users believe a technology is effortless to use, encompassing aspects of compatibility, simplicity, and self-efficacy (Davis, 1989). The TAM framework posits that PEOU affects PU, since technologies that are easier to navigate tend to be viewed as more beneficial (Schillewaert et al., 2005). Therefore, the following hypothesis can be formulated:

H8: Perceived ease of use has a positive effect on perceived usefulness.

Increased PEOU has a positive impact on technology acceptance, as users are more likely to adopt accessible and user-friendly technologies (Agarwal and Karahanna, 2000; Davis, 1989; Hunter, 2019). This connection suggests that usability directly influences the intent to adopt AI. PU reflects users' belief that a system will improve work performance (Davis, 1989; Saci, 2021), encompassing factors such as subjective standards, image, and work relevance (Venkatesh & Bala, 2008). Users assess usefulness by comparing the capabilities of a system to their business requirements, leading to a positive relationship between PU and intention to adopt. This connection leads to the following hypotheses:

- H9: Perceived ease of use positively influences the intention to adopt AI.
 H10: Perceived usefulness positively influences intention to adopt AI.

RESEARCH METHODOLOGY

Research Instrument

The conceptual model and hypotheses were empirically validated through a quantitative survey. To this end, a structured questionnaire was developed by identifying constructs from the established literature on the TOE and TAM frameworks. Items were adapted from previously validated measurement scales to represent each construct in the proposed research model. To ensure instrument validity, a two-stage validation process was employed. First, an initial draft was reviewed by a panel of academic experts in AI, information systems, and quantitative methodology, leading to refinements for clarity and content validity. Subsequently, a pilot test was conducted with a small group of IT specialists and senior accounting professionals (not included in the final sample) to confirm the instrument's clarity, contextual appropriateness, and reasonable completion time. The final questionnaire, presented in Table 1, comprised 30 items covering all relevant constructs: PCS, PCM, TR, IF, FR, COA, SV, PU, PEOU, and intention to adopt AI (IAA). Responses were collected on a five-point Likert scale, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

Table 1. Measurement Instruments of the Structured Questionnaire

Items		Sources
Perceived cost (PCS)		
PCS1	Implementing an artificial intelligence (AI)-based system is very expensive.	Maduku et al. (2016)
PCS2	The amount of money invested in training employees on an AI-based system would be very high.	Pillai et al., (2022)
PCS3	The platform, control systems safety enclosure, and mounting arrangement require huge investment for AI-based systems.	
Perceived compatibility (PCM)		
PCM1	We have a good plan to integrate an AI-based system with existing practices in our company.	Peng et al. (2012)
PCM2	AI technology is compatible with existing technological architecture of our company.	Géczy et (2012)
PCM3	Customization in AI-based system is easy.	
Trust in technology (TR)		

continued on following page

Table 1. Continued

Items		Sources
TR1	AI technology is reliable.	Chatterjee et al. (2021)
TR2	Employees will trust the AI technology in our company.	
TR3	AI technology is trustworthy.	
Infrastructure and capabilities (IF)		
IF1	The physical information technology infrastructure within our company is sufficient for supporting an AI-based system.	Lai et al. (2018)
IF2	When implementing an AI-based system, the company will have sufficient supporting staff.	
IF3	When implementing an AI-based system, the company will have sufficient support in training.	
Financial readiness (FR)		
FR1	The company would have the financial resources to adopt an AI-based system.	Lai et al. (2018)
FR2	Our financial budgets would be significant enough to support the adoption of an AI-based system.	
FR3	It would be easy to obtain financial support from local banks and/or other financial institutions to adopt an AI-based system.	
Competitive advantage (COA)		
COA1	I am aware that an AI-based system is being implemented by a few of our competitors.	Rogers (2003)
COA2	I understand that by using an AI-based system, our company will have a competitive advantage.	Yang et al. (2019)
COA3	I am aware that many companies are moving toward AI-based systems.	Makridakis (2017)
Support from vendors (SV)		
SV1	There would be adequate technical support for an AI-based system provided by vendors.	Maduku et al. (2016)
SV2	Training for AI-based systems would be adequately provided by vendors and other training service providers.	
SV3	AI Technology vendors are encouraging our company to adopt an AI-based system by providing us with free training sessions.	
Perceived usefulness (PU)		
PU1	Using an AI-based system would make our company more efficient.	Gangwar et al. (2015)
PU2	Using an AI-based system would increase productivity in our company.	
PU3	Using an AI-based system would enable us to accomplish organizational task more quickly.	
Perceived ease of use (PEOU)		

continued on following page

Table 1. Continued

Items		Sources
PEU1	The procedure of using AI-based systems is understandable.	Gangwar et al. (2015)
PEU2	It is easy to learn how to use AI-based systems.	
PEU3	It is easy to make use of AI-based systems.	
Intention to adopt AI (IAA)		
IAA1	I think AI-based systems are advantageous.	Yousafzai et al. (2007)
IAA2	I am in favor of using AI-based systems.	
IAA3	I would like to use an AI-based system to its full potential.	

Sampling and Data Collection

A purposeful sampling strategy was used for data collection, targeting accounting professionals in the French professional services sector. An online survey was distributed via email to professionals at 617 accounting firms. The communication informed prospective respondents of the study's academic purpose, provided clear ethical guidelines, and assured them of strict anonymity and confidentiality. From this initial sampling a total of 294 responses were received. After 56 responses were excluded for incompleteness, a final dataset of 238 valid responses was established, resulting in an effective response rate of 38.57%. This rigorous and ethically grounded procedure ensured that the dataset accurately captured the professional expertise and organizational realities relevant to AI adoption in the French accounting sector. The demographic information for the respondents is presented in Table 2.

Table 2. Sample Profile (N = 238)

Category	Item	Frequency	Percentage
Gender	Female	54	23%
	Male	184	77%
	Total	238	100%
Age	< 25	38	16%
	25–35	104	44%
	36–45	79	33%
	> 46	17	7%
	Total	238	100%
Respondent title	Chartered accountant	94	39%
	Trainee chartered accountant	56	24%
	Accounting associate	88	37%
	Total	238	100%
Number of employees in the firm	<10	31	13%
	10–50	95	40%
	51–250	112	47%
	Total	238	100%

Data Analysis Technique

The study used the partial least squares method of SEM to test the hypotheses and validate the model, (Jasimuddin et al., 2015). The partial least squares–SEM (PLS–SEM) method was chosen for its ability to efficiently analyze complex models (Hair et al., 2023; Jasimuddin et al., 2017). Unlike covariance-based SEM, PLS–SEM does not require data to follow a normal distribution, which is a critical condition for covariance-based SEM application (Hride et al., 2021; Huo et al., 2022; Jasimuddin et al., 2015, 2017, 2019; Li et al., 2024; Rahman, Hossain, et al., 2022; Rahman, Islam, et al., 2022; Ringle et al., 2012). In addition, this technique can be used without any limitation on sample size (Willaby et al., 2015; Jasimuddin et al., 2019; Xia et al., 2023).

RESULTS ANALYSIS

Measurement Properties and Discriminant Validity Test

The loading factor for each indicator was assessed, and all values exceeded the recommended threshold of 0.70 to estimate the convergent validity of all items (Chin, 2009). To evaluate the constructs’ reliability and validity, composite reliability and AVE were calculated, with all values greater than 0.80 and 0.50, respectively (Hair et al., 2023). Potential multicollinearity was examined using the variance inflation factor, and all variance inflation factor values were within acceptable limits (Kock & Lynn, 2012). The results are reported in Table 3. Moreover, this analysis yielded the validated measurement model shown in Figure 2.

Table 3. Measurement Model Assessment

Constructs / Item	LF	AVE	CR	α	VIF	Convergent validity (t-stat)
Perceived compatibility (PCM)		0.732	0.942	0.83		
PCM1	0.855				2.278	23.834
PCM2	0.815				2.184	17.571
PCM3	0.896				1.619	35.932
Perceived cost (PCS)		0.765	0.907	0.854		
PCS1	0.911				2.347	27.425
PCS2	0.902				2.039	27.941
PCS3	0.807				2.031	11.85
Trust in technology (TR)		0.748	0.899	0.862		
TR1	0.826				3.172	13.677
TR2	0.935				1.679	35.061
TR3	0.829				3.173	13.398
Infrastructure and capabilities (IF)		0.733	0.891	0.837		
IF1	0.904				1.554	29.103
IF2Model	0.834				2.642	16.98
IF3	0.828				2.613	16.144
Financial readiness (FR)		0.737	0.894	0.831		
FR1	0.816				2.123	22.356

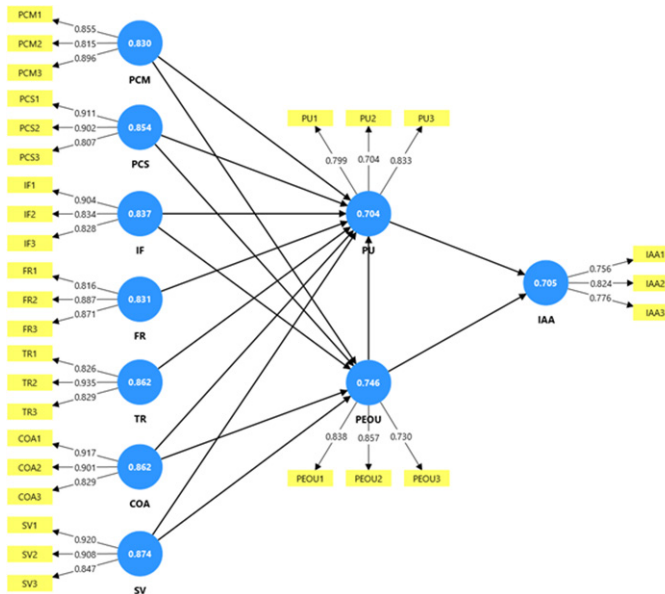
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Table 3. Continued

Constructs / Item	LF	AVE	CR	α	VIF	Convergent validity (t-stat)
FR2	0.887				1.641	46.608
FR3	0.871				2.324	34.862
Competitive advantage (COA)		0.78	0.914	0.862		
COA1	0.917				2.392	9.727
COA2	0.901				2.265	8.35
COA3	0.829				2.022	6.753
Support from vendors (SV)		0.796	0.921	0.874		
SV1	0.92				2.715	17.571
SV2	0.908				2.318	17.011
SV3	0.847				2.201	10.764
Perceived usefulness (PU)		0.61	0.823	0.704		
PU1	0.799				1.827	20.398
PU2	0.704				1.64	12.782
PU3	0.833				1.214	28.574
Perceived ease of use (PEOU)		0.657	0.851	0.746		
PEOU1	0.838				2.347	19.185
PEOU2	0.857				2.039	26.784
PEOU3	0.73				2.031	13.763
Intention to adopt AI		0.617	0.829	0.705		
IAA1	0.756				1.566	17.983
IAA2	0.824				1.22	27.422
IAA3	0.776				1.572	18.696

Note: LF- loading factor; AVE= average variance extracted; CR = composite reliability; VIF= variance inflation factor

Figure 2. Measurement Model



Furthermore, the square roots of the AVE (ranging from 0.78 to 0.89) were higher than the corresponding inter-construct correlations, satisfying the Fornell–Larcker criterion (Fornell & Larcker, 1981) and confirming discriminant validity (see Table 4). Although the correlation between PU and IAA was relatively high (0.596), it remained below the AVE square roots, indicating adequate construct distinctiveness. The bootstrap procedure (5,000 resamples) confirmed the significance of the loadings and structural paths, while blindfolding verified the predictive relevance (Q^2) of the endogenous constructs. Overall, the measurement model demonstrates satisfactory reliability, validity, and predictive power.

Table 4. Assessment of Discriminant Validity Test (Fornell and Larcker Criterion)

	COA	FR	IAA	IF	PCM	PCS	PEOU	PU	SV	TR
COA	0.883									
FR	-0.038	0.858								
IAA	0.17	0.268	0.786							
IF	0.002	0.102	0.319	0.856						
PCM	-0.114	0.127	0.311	0.159	0.856					
PCS	-0.041	0.062	-0.148	-0.004	-0.01	0.875				
PEOU	0.13	0.053	0.276	0.091	0.176	-0.219	0.81			
PU	0.085	0.438	0.569	0.353	0.371	-0.077	0.16	0.781		
SV	0.003	0.714	0.044	-0.101	-0.081	0.029	0.057	0.177	0.892	
TR	-0.013	0.107	0.205	0.204	0.17	-0.097	-0.005	0.34	-0.118	0.865

Hypotheses Testing (SEM)

The study hypotheses were tested using PLS–SEM. The bootstrap procedure (5,000 resamples) was applied to estimate the path coefficients, t-values, and p-values, providing a robust non-parametric assessment of the model’s statistical significance (Chin, 2009). Subsequently, the blindfolding procedure was conducted to assess the predictive relevance (Q^2) of the endogenous constructs. This analysis yielded the validated structural model shown in Figure 3, and Table 5 presents the corresponding path coefficients, t-values, p-values, and explained variance (R^2) for each relationship in the model.

Figure 3. Structural Model Results

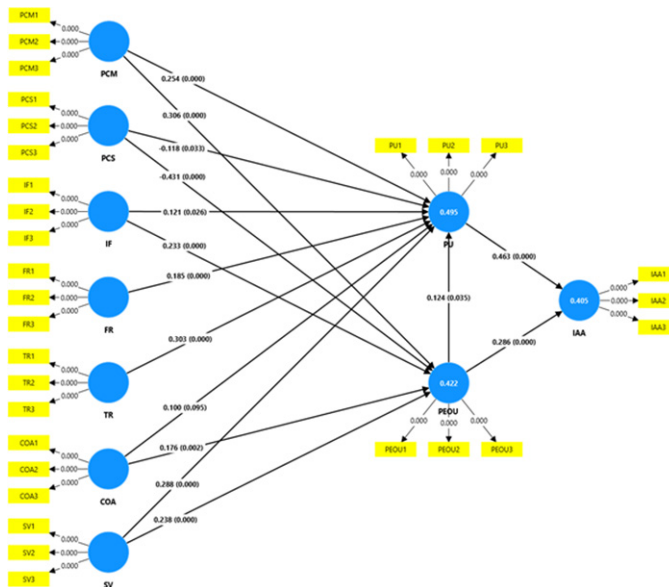


Table 5. Structural Model

Linkages	Hypotheses	Path coefficient (β)	STDEV	T-values	P-values	Sign	Findings
Effects on PU		$R^2=0.495$					
by PCM	H1a	0.254	0.049	5.135	***	+	Supported
by PCS	H2a	-0.118	0.055	2.138	*	-	Supported
by TR	H3	0.303	0.051	5.965	***	+	Supported
by IF	H4a	0.121	0.054	2.227	*	+	Supported
by FR	H5	0.185	0.052	3.542	***	+	Supported
by COA	H6a	0.100	0.060	1.672	ns	+	Not Supported
by SV	H7a	0.288	0.050	5.724	***	+	Supported
by PEOU	H8	0.124	0.059	2.113	*	+	Supported
Effects on PEOU		$R^2=0.422$					
by PCM	H1b	0.306	0.047	6.471	***	+	Supported

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Table 5. Continued

Linkages	Hypotheses	Path coefficient (β)	STDEV	T-values	P-values	Sign	Findings
Effects on PU		R²=0.495					
by PCS	H2b	-0.431	0.049	8.835	***	-	Supported
by IF	H4b	0.233	0.052	4.463	***	+	Supported
by COA	H6b	0.176	0.056	3.140	**	+	Supported
by SV	H7b	0.238	0.047	5.073	***	+	Supported
Effects on IAA		R²=0.405					
by PEOU	H9	0.286	0.051	5.638	***	+	Supported
by PU	H10	0.463	0.049	9.457	***	+	Supported

Note. (ns) = not significant; *p < 0.05; **p < 0.01; ***p < 0.001.

RESULTS

As expected, hypotheses H9 and H10 were supported in that both PEOU and PU had a significant positive effect on behavior intention. Together, they accounted for 40.5% of the variance in behavior intention, with PU ($\beta = 0.463$) contributing more to intention than PEOU ($\beta = 0.286$). PEOU also had a positive effect on PU ($\beta = 0.124$). Therefore, H8 was supported. Thus, the total effect of PEOU on behavior intention was 0.34 ($= 0.286 + 0.124 * 0.463$). Even after the indirect effect was accounted for, PU still had a stronger explanatory power of IAA than PEOU (0.463 versus 0.34).

As for the paths from the variables of the TOE framework to the TAM constructs, the results show that all the hypotheses were found to be significant except H6a. Between the impacts of PCM, PCS, IF, FR, TR, and SV on PU, the impact of TR on PU (H3) was the highest, as the concerned path coefficient was 0.303, with a level of significance of $p < 0.001$ (***). These factors explained 49.5 percent of the variance in PU. Between the impacts of PCM, PCS, IF and SV on PEOU, the impact of PCS on PEOU (H2b) was the highest, as the concerned path coefficient was 0.431, with a level of significance of $p < 0.001$ (***). These variables explained 42.2 percent of the variance in PEOU.

DISCUSSION AND IMPLICATIONS

This research investigated how the facilitating and inhibiting factors influence organizations' IAA in their accounting processes. Using an integrated TAM–TOE model, technological, organizational, environmental factors were proposed to have significant influence on IAA via PU and PEOU.

The study highlights that PEOU positively impacts PU (H8). PEOU and PU were found to be significant antecedents of IAA by accounting professional (H9 and H10), with PU exerting a stronger influence than PEOU. These results conform with the concept of TAM (Davis, 1989) and align with earlier evidence regarding the use of cloud-based accounting applications (Le and Cao, 2020; Tarmidi et al., 2014) and the adoption of AI in accounting (Damerji and Salimi, 2021).

In terms of technological context, PCM was shown to have a positive effect on both PEOU (H1a) and PU (H1b). This finding aligns with the findings of Peng et al. (2012) and Gangwar et al. (2015) and partially with those of Chatterjee et al. (2021). The positive link between PCM and PEOU suggests that when AI technology is highly compatible, users do not need to make significant modifications to existing auditing tools and accounting systems for effective adoption. The results indicate that PCS exerts a strong negative effect on both PU and PEOU (supporting H2a and H2b), highlighting cost as a critical barrier to AI adoption in the French accounting sector. As technology costs rise, its perceived value and usability decline (Premkumar et al., 1997) since users tend to view expensive

systems as both less useful and more difficult to integrate. This dynamic is amplified in the case of AI, which requires significant organizational investment in platforms, control systems, safety features, infrastructure, consultancy, and training (Sangomla, 2019). Such financial burdens translate directly into operational complexity and create psychological barriers, as high expenditures are associated with greater risk and organizational effort, thereby undermining perceptions of effortlessness. In knowledge-intensive fields where firms face budget constraints despite the need for advanced systems, this finding underscores that simplifying software alone is insufficient; vendors must also address total cost of ownership and financial accessibility, since cost ultimately acts as a gatekeeper to both usability and perceived value. The study also finds that TR is the strongest positive antecedent of PU (H3), confirming that trust in technological integrity is central to adoption in professional contexts. In a finding consistent with prior research (Ha & Stoel, 2009; Suh & Han, 2002), trust enhances users' confidence that AI can support their objectives by ensuring accuracy, transparency, and security in handling sensitive financial data and regulatory tasks. Trust thus reduces the perceived risks, learning effort, and monitoring demands associated with new systems, making professionals more willing to rely on AI and recognize its value. The strong path coefficient for TR highlights that professionals are willing to adopt complex systems only if they believe those systems are reliable enough to support the fiduciary and ethical duties of their profession.

For organizational context, the results show that FR and IF have a positive impact on PU, supporting Hypotheses H4a. This finding is in line with previous research (Ransbotham et al., 2017), which suggests that with the availability of adequate financial and technical resources and trained employees, there are no barriers to adopting innovative technology. Additionally, IF is also found to positively influence PEOU (H4b), aligning with earlier findings (Aboelmaged, 2014; Gusev, 2020). This connection may be due to the specific nature of AI practices, which rely on highly advanced networks and systems. This finding is also in agreement with previous studies indicating that skills and technical capabilities are critical factors in facilitating AI acceptance and the effective integration of new technologies like AI (Chen, 2019; Garrison et al., 2015). Effective IT development strategies, along with adequate skills and technical knowledge, will ensure the smooth integration of AI into business or service activities. Conversely, a lack of skill and technical expertise may lead potential users to reject AI, hindering the organization's successful adoption. Consequently, future professionals in accounting and finance are expected to possess diverse skills and engage in continuous learning (Norzelan et al., 2024). FR positively affects PU, supporting Hypothesis H5. This finding confirms the finding of an earlier study by Yang et al. (2024). If appropriate financial resources are available, there will be no impediment to adopting AI in professional services.

As such, FR emerges as a core determinant of AI readiness, influencing not only the choice and implementation of AI tools but also a firm's ability to overcome technological and organizational constraints in the adoption process (Yang et al., 2024).

With respect to the environmental context, COA did not exert a significant influence on PU (H6a), in contrast to the findings of Chatterjee et al. (2021). It is critical to note, however, that COA did positively affect PEOU use (Chatterjee et al., 2021; Curran and Purcell, 2017). This divergence suggests that while market pressures may facilitate adoption by rendering AI seemingly easier to use, they do not translate into stronger perceptions of its personal utility for individual professionals. PU appears instead to be more directly shaped by improvements in daily tasks and workflow efficiency and by technology-specific factors such as intrinsic capabilities and reliability. This interpretation is consistent with the model, in which TR and PCM emerged as significantly stronger predictors of PU. A further explanation may lie in sectoral conditions: In French accounting, where digitalization mandates (e-invoicing/dematerialization) are exogenous, adoption is driven less by COA than by regulatory compliance and operational necessity. Furthermore, SV significantly enhances both PU and PEOU, confirming H7a and H7b. This finding is consistent with prior research by Haans et al. (2016), which highlighted the role of partner support in facilitating knowledge sharing and providing financial resources, thereby strengthening employees' capacity to adopt innovative

technologies. VS remains critical throughout the adoption process, with comprehensive training identified as a key requirement for the smooth and effective integration of AI in accounting (Pillai & Sivathanu, 2020).

Implications for Theory

Our study offers several theoretical contributions. First, it extends the application of the TAM and the TOE framework by integrating them into a unified model that captures both individual-level perceptions and broader organizational and environmental factors. While TAM traditionally focuses on individual-level perceptions of a technology's PU and PEOU and the TOE framework offers a broader view of technological, organizational, and environmental factors, this research combines their strengths by using the TAM constructs as mediators. Specifically, the model posits that external TOE factors, such as PCM, TR, IF, FR, COA, and VS, do not directly influence IAA. Instead, they first shape an individual's PU and PEOU, which are the direct drivers of adoption intention. This integrated approach provides a holistic perspective that simultaneously considers both individual psychological factors and the broader strategic and contextual realities that are crucial for successful AI implementation in a professional service environment.

Second, this research contributes to the relatively underexplored context of AI adoption in accounting, a field characterized by complex, knowledge-intensive workflows and stringent regulatory requirements. By empirically validating the influence of variables such as PCM, PCS, TR, IF, FR, VS, and COA, the study offers a nuanced understanding of how both facilitating and inhibiting factors interact with user perceptions (PU and PEOU) to shape adoption intentions.

Third, the findings reveal mediating roles of PU and PEOU, clarifying the mechanisms through which external factors influence behavioral intention. This observation supports the extension of TAM constructs beyond technology usability, emphasizing their relevance in mediating strategic and resource-based considerations in AI adoption. Additionally, the study introduces PCS as a negative driver, a relatively underexamined barrier in AI research, highlighting its detrimental effect on ease of use and usefulness perceptions.

Finally, by focusing on French accounting firms, this study provides context-specific insights, enriching global discourse with localized empirical evidence. It bridges a gap in the literature by addressing AI adoption in professional service firms in continental Europe, where organizational structures, digital maturity, and regulatory environments may differ from commonly studied Anglo-American contexts.

Implications for Practice

This study provides a clear and empirically grounded framework for managers, accounting professionals, and AI vendors to accelerate AI adoption in accounting firms. The results highlight that PU and PEOU are the main drivers of accountants' IAA and that these perceptions are shaped by factors such as TR, PCM, IF, FR, and VS.

Accordingly, managers should prioritize building trust and compatibility by selecting AI tools that integrate seamlessly with existing workflows and by fostering transparent communication on their reliability, privacy, and security. Vendors should support these efforts through live demonstrations, success stories, and clear documentation of system safeguards to reduce perceived risks.

At the same time, both firms and vendors must manage PCS proactively, as financial concerns remain one of the most significant barriers to adoption. High PCS can make AI seem overly complex or inaccessible, undermining even user-friendly designs. To mitigate this effect, AI providers should emphasize value-for-money, offer transparent return-on-investment projections, and propose affordable models such as SaaS solutions or shared investment schemes.

Practitioners should also reinforce organizational readiness by investing in robust IT infrastructure and ensuring adequate financial resources to sustain AI deployment. Systems should be regularly updated and secured against vulnerabilities to maintain data integrity and compliance.

Finally, the study underscores the importance of human capital and collaboration. Accounting firms should invest in digital upskilling and targeted training programs to enhance AI competence and acceptance, while vendors should provide comprehensive implementation and training support. Collaboration between technical experts and accounting professionals is vital to ensure that AI solutions remain relevant, practical, and aligned with professional needs.

By systematically addressing these priorities, cost, trust, readiness, compatibility, and people, organizations can overcome adoption barriers, strengthen digital resilience, and fully harness the transformative potential of AI in the accounting profession.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study aimed to investigate the acceptance of AI technology among accounting professionals using the TAM and TOE frameworks. A structured questionnaire was used to conduct a cross-sectional study of accounting firms in France. AI is increasingly being adopted by professional service firms in various fields, including accounting (Damerji and Salimi, 2021), law (Remus and Levy, 2017), and healthcare (Sun and Medaglia, 2019). Despite these advancements, the journey of AI adoption is complex. Recent research has indicated that more than half of AI projects do not fulfill their promises to the adopting organizations (Vial et al., 2023). Therefore, both practitioners and researchers must understand the factors influencing AI adoption. To ground these factors in existing literature, we developed and empirically tested a hybrid model based on the TOE and TAM frameworks. The TAM framework helped identify technological challenges, while the TOE framework highlighted socio-environmental issues. This model extends TAM by integrating TOE variables pertinent to AI adoption as external variables, such as PCM, PCS, IF, FR, TR, COA, and VS, each having a direct effect on one or both of the TAM constructs and indirectly affecting adoption. Thus, the two TAM constructs serve as mediators for these external variables. Given the limited research on AI adoption in organizations from a socio-environmental perspective with a focus on technological aspects, this study can be considered a significant effort.

This study provides valuable insights into AI adoption in professional services sectors, particularly in accounting. However, our research has limitations. One of these lies in the generalizability of our findings. Although the results are discussed in a general context, the specific characteristics of certain professions, such as unique knowledge requirements and distinct governance structures, may have different impacts on AI adoption. Therefore, organizations in various professional services sectors may encounter subtle differences in the factors influencing AI adoption. Further empirical research in fields other than accounting is therefore needed to verify or refute these findings. The study also notes that the model's predictive accuracy ranges from 40.5% to 49.5%. Future research could consider moderating variables such as firm size. Firms of different sizes may face different challenges. Future research could also explore other boundary conditions to determine whether incorporating them can improve the model's predictive capabilities. For example, the model does not consider the impact of transaction costs on IAA, which could make it more practical and attractive.

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COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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