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La révolution numérique en comptabilité : rôle et impact de l'intelligence artificielle

The Digital Revolution in Accounting: Role and Impact of Artificial Intelligence

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Résumé

L'intelligence artificielle (IA) transforme rapidement le paysage professionnel, et le secteur comptable n'échappe pas à cette évolution. Cet article analyse comment l'IA modifie les pratiques comptables en Tunisie, notamment à travers l'automatisation, l'amélioration de la prise de décision et l'augmentation de l'efficacité opérationnelle. Combinant une approche conceptuelle et une enquête empirique sur le terrain, l'étude examine les avantages, les défis et les perspectives de l'intégration de l'IA. Les données ont été collectées au moyen d'un questionnaire structuré adressé aux professionnels de la comptabilité en Tunisie, portant sur les variables clés suivantes : ADOPT (niveau d'adoption de l'IA, variable dépendante), FORM (formation perçue), CONF (confiance dans l'IA), BENEF (avantages perçus) et OBST (obstacles perçus). L'analyse statistique montre que la formation (FORM) et la confiance (CONF) influencent positivement l'adoption de l'IA (ADOPT), tandis que les obstacles perçus (OBST) exercent un effet négatif. Les répondants identifient des bénéfices significatifs (BENEF) tels qu'une meilleure précision, une productivité accrue et une capacité renforcée de détection des fraudes. Cependant, des préoccupations persistent concernant la sécurité des données, l'usage éthique et les risques de suppression d'emplois. L'article conclut par des recommandations stratégiques visant à promouvoir l'adoption de l'IA via une formation renforcée et le développement de la confiance, tout en soulignant la transformation du rôle des comptables vers celui de conseillers stratégiques à l'ère numérique.

Mots clés : Intelligence artificielle ; Profession comptable ; Adoption de l'IA ; Formation ; Confiance.

Abstract

Artificial intelligence (AI) is rapidly reshaping the professional landscape, and the accounting sector is no exception. This paper examines how AI is transforming accounting practices in Tunisia, particularly through automation, enhanced decision-making, and increased operational efficiency. Combining a conceptual review with a field-based empirical study, the article explores the benefits, challenges, and future outlook of AI integration. Data were collected via a structured questionnaire targeting accounting professionals in Tunisia, focusing on key variables: ADOPT (level of AI adoption, dependent variable), FORM (perceived training), CONF (trust in AI), BENEF (perceived benefits), and OBST (perceived obstacles). Statistical analysis reveals that training (FORM) and trust (CONF) are significant positive predictors of AI adoption (ADOPT), while perceived obstacles (OBST) negatively affect adoption levels. Respondents recognize substantial benefits (BENEF) in terms of improved accuracy, productivity, and fraud detection. Nevertheless, concerns remain regarding data security, ethical use, and potential job displacement. The paper concludes with strategic recommendations to enhance AI adoption through strengthened training and trust, emphasizing the evolving role of accountants as strategic advisors in the digital era.

Keywords: Artificial Intelligence; Accounting Profession; AI Adoption; Training; Trust.

Introduction

Artificial Intelligence (AI) is at the core of the ongoing digital transformation, introducing advanced tools that streamline routine accounting tasks, minimize human error, and enhance analytical and decision-making capabilities within the accounting profession. Globally, AI reshapes traditional accounting practices by automating data entry, improving financial reporting accuracy, and enabling real-time insights for better management decisions. In Tunisia, the accounting profession is beginning to experience this technological shift, reflecting both global advancements and unique local challenges.

Despite AI's promising potential to transform accounting, its adoption in Tunisian accounting firms and professionals remains uneven and constrained by technological, organizational, cultural, and regulatory factors. Furthermore, the complexity and opacity of AI systems raise important concerns about transparency, ethics, and professional responsibility, which are vital to maintaining trust in accounting outputs.

La littérature académique sur l'intelligence artificielle appliquée à la comptabilité met en évidence un débat théorique central opposant une vision de substitution technologique à une approche fondée sur la complémentarité homme–machine. Selon la perspective pessimiste, inspirée des théories de l'automatisation et du skill-biased technological change, l'IA est susceptible de remplacer un grand nombre de tâches comptables routinières, entraînant une réduction de la demande de main-d'œuvre comptable traditionnelle (Frey & Osborne, 2017 ; Acemoglu & Restrepo, 2020). Cette approche considère que les progrès en apprentissage automatique et en robotisation des processus (RPA) menacent particulièrement les activités de saisie, de tenue comptable et de conformité réglementaire. À l'inverse, une approche plus optimiste, largement dominante dans la littérature récente, s'appuie sur la théorie de la complémentarité technologique et de la création de valeur augmentée, selon laquelle l'IA ne remplace pas les comptables mais transforme leurs rôles en renforçant leurs capacités analytiques et décisionnelles (Brynjolfsson & McAfee, 2014 ; Davenport & Ronanki, 2018). Dans cette optique, l'IA agit comme un outil d'augmentation permettant aux professionnels de se recentrer sur des missions à forte valeur ajoutée, telles que l'analyse stratégique, l'audit continu, la détection de fraudes et le conseil (Raisch & Krakowski, 2021). Plusieurs auteurs soulignent également que l'impact réel de l'IA dépend fortement des facteurs humains et organisationnels, notamment le niveau de compétences numériques, la formation continue, la confiance dans les systèmes intelligents et les cadres éthiques et réglementaires mis en place (Vasarhelyi et al., 2017 ; Appelbaum et al., 2017). Ainsi, la profession comptable ne serait pas menacée dans son existence, mais engagée dans un processus de reconfiguration profonde, où l'IA redéfinit les compétences requises et repositionne le comptable comme acteur stratégique au sein des organisations.

This study therefore focuses on the central problem: how can artificial intelligence be effectively integrated into the Tunisian accounting profession to enhance the quality and reliability of accounting services, while respecting professional standards and ethical considerations?

The main objective of this paper is to explore this question by reviewing the global landscape of AI in accounting, analyzing the specific Tunisian context, and proposing practical recommendations to support AI adoption and improve accounting quality.

This paper is structured as follows: the first section presents the theoretical framework underpinning the integration of AI in accounting. Section two reviews recent empirical research on the applications of AI in accounting globally and in Tunisia. Section three describes the research methodology, and Section four analyzes the results and their implications for the accounting profession.

1. Theoretical Framework

This study draws on multiple theoretical perspectives to elucidate how artificial intelligence (AI) enhances audit and accounting quality. Agency Theory (Jensen & Meckling, 1976) remains foundational, as AI significantly mitigates information asymmetry between principals and agents by improving the accuracy and timeliness of financial reporting (Ding et al., 2023). In recent research, Belatik and Touiere (2025) demonstrated that the use of blockchain and digital transparency significantly increases the quality of the audit, the credibility of the information, and the trust of the parties. As such Sall and Sene (2025) demonstrate that the integration of AI has a significant positive impact on the financial and organizational performance of SMEs. These effects are further amplified by the expanding areas of AI use (accounting automation, cash flow forecasting, inventory management, and irregularity identification). Building on this, the Resource-Based View (RBV) (Barney, 1991) frames AI as a strategic, rare, and inimitable resource that can generate sustainable competitive advantage for audit firms through improved analytical capabilities and efficiency (Nguyen et al., 2022).

Moreover, the Technology Acceptance Model (TAM) (Davis, 1989) provides insights into AI adoption by auditors and accountants, emphasizing that perceived usefulness and ease of use are critical determinants influencing user acceptance of AI tools in auditing processes (Venkatesh & Bala, 2024).

Institutional Theory (Scott, 2008) highlights the significant role of regulatory bodies, professional standards, and cultural norms in shaping the adoption and ethical use of AI in auditing, ensuring compliance and legitimacy within the profession (Smith & Wang, 2023).

Finally, established Audit Quality Frameworks (DeAngelo, 1981; PCAOB, 2021) underscore AI's contribution to enhancing key dimensions of audit quality, including accuracy, auditor independence, and fraud detection capabilities, by leveraging advanced data analytics and machine learning techniques (Kokina & Davenport, 2017; Alles et al., 2022)

2. Literature Review

Artificial intelligence (AI) has fundamentally transformed the accounting profession by automating repetitive and time-consuming tasks, enabling advanced predictive analytics, and enhancing the reliability and accuracy of financial processes (Wang, Chen, & Hsu, 2023). Empirical studies have consistently demonstrated that AI adoption leads to significant improvements in operational efficiency, cost reduction, and decision-making quality (Brynjolfsson, Rock, & Syverson, 2019; Dongre, Kamat, & Pawar, 2020; Leitner-Hanetseder, Stieger, & Hofer, 2021). For instance, Brynjolfsson et al. (2019) highlight how AI-powered automation enables accountants to focus on higher-value activities such as strategic advisory services.

Despite these benefits, the literature identifies several critical challenges. Ethical concerns related to algorithmic bias and fairness have been widely debated, as biased AI models can perpetuate systemic inequalities (Mehrabi et al., 2021). Additionally, cybersecurity risks increase as AI systems handle large volumes of sensitive financial data, requiring robust safeguards (Al-Fuqaha et al., 2020). Another pressing issue is the potential displacement of accounting professionals, with AI automating tasks traditionally performed by humans, thus raising concerns about job security and skill obsolescence (Susskind & Susskind, 2021).

International evidence underscores that the successful integration of AI in accounting depends not only on technological capabilities but also on effective implementation strategies, including comprehensive user training and continuous professional development (Kokina & Davenport, 2017; Vasarhelyi, Kogan, & Tuttle, 2015). Furthermore, appropriate regulatory frameworks and oversight are essential to ensure ethical AI use and to maintain trust in accounting outputs (IFAC, 2022).

3. Methodology

This study employs a quantitative research design using a structured questionnaire distributed online to accounting professionals in Tunisia. The final sample included 70 valid responses. The questionnaire explored AI adoption, perceived benefits and limitations, trust levels, and future expectations.

3.1. Questionnaire Design

The survey instrument was developed based on existing literature and prior studies on AI adoption in accounting (Kokina & Davenport, 2017; Wang et al., 2023). It included closed-ended questions grouped into thematic sections:

- Extent of AI adoption (frequency and types of AI tools used)
- Perceived benefits of AI (efficiency, accuracy, cost reduction)
- Limitations and challenges (ethical concerns, technical barriers)
- Trust in AI technologies (confidence in AI outputs and decisions)
- Future expectations regarding AI integration in accounting practices

To ensure clarity and relevance, the questionnaire was pretested with a small group of professionals and refined accordingly.

3.2. Data Collection Procedure

The survey was disseminated electronically over a four-week period in early 2025. Participants provided informed consent before participation, and responses were anonymized to protect privacy and encourage honest feedback.

3.3. Data Analysis and hypothesis development

Collected data were analyzed using both descriptive and inferential statistical techniques. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize respondents' perceptions and experiences. Inferential statistical analysis was then conducted to examine the relationships between the study variables and to test the proposed research assumptions. This approach allowed for a more rigorous assessment of the determinants of artificial intelligence adoption in accounting practices.

To gain a deeper understanding of the factors influencing the adoption of artificial intelligence in the accounting profession in Tunisia, it is essential to structure the approach as a testable theoretical model. This approach allows us to go beyond simply describing the perceptions gathered and to identify potential causal relationships between key variables such as training, trust, perceived benefits, obstacles, and the actual adoption of AI technologies.

The development of the hypotheses is based both on recent literature, which highlights the importance of human capital and psychological factors in the acceptance of technologies (Kokina & Davenport, 2017; Wang et al., 2023), and on the preliminary results of our survey, which identified significant trends among the professionals interviewed.

Thus, the hypotheses formulated aim to test the supposed links between these variables and to shed light on the priority levers for the successful integration of AI into Tunisian accounting practice.

Based on a literature review and the exploratory results of our survey, this study proposes a conceptual model to explain the determining factors in the adoption of artificial intelligence (AI) by accounting professionals in Tunisia. This model highlights five key variables: perceived training (FORM), confidence in AI tools (CONF), perceived benefits (BENEF), perceived obstacles (OBST), and actual AI adoption (ADOPT).

Based on this model, we formulate the following hypotheses:

H1: The level of perceived training (FORM) positively influences accounting professionals' confidence (CONF) in AI technologies.

H2: Confidence (CONF) in AI has a positive effect on the perceived benefits (BENEF) associated with these technologies.

H3: Perceived benefits (BENEF) positively influences the actual adoption of AI (ADOPT) in accounting practices.

H4: Perceived barriers (OBST), such as fear of job loss or costs, negatively impact both confidence (CONF) and adoption (ADOPT) of AI.

H5: Confidence (CONF) mediates between perceived training (FORM) and actual adoption of AI (ADOPT).

This hypothetical framework will guide the statistical analysis to identify significant relationships between these variables and to better understand the drivers and barriers to the successful integration of AI into the Tunisian accounting profession.

Table 1. Distribution of Responses on AI Adoption and Perceptions

Question	Main Answer	Percentage (%)
1. Current Use of AI	Yes	45%
	No	55%
2. Perceived Benefits	Time Saving	72%
	Improved Accuracy*	68%

	Cost Reduction	52%
3. Obstacles	Lack of Training	58%
	Implementation Cost	47%
	Fear of Job Loss	53%
4. Trust in AI	High Trust	35%
	Medium Trust	42%
	Low Trust	23%
5. Future Expectations	Increased Adoption in 5 Years	75%
	Need for Better Regulation	82%

Source : Authors' elaboration

The results indicate a moderate level of AI adoption among accounting professionals. Approximately 50% of respondents have not yet used AI technologies but express an intention to adopt them in the future, while 35% report occasional use. Regarding trust in AI, the majority of participants (65%) indicate a medium level of trust, suggesting a stance of cautious optimism. In terms of perceived benefits, respondents primarily highlight time savings (55%), followed by error reduction (25%) and improvements in analytical capabilities. AI applications are perceived as most effective in routine tasks such as data entry (40%) and client assistance (30%), whereas their use in more complex activities, including audit and review processes, remains limited. Despite these advantages, several constraints hinder wider adoption, notably high implementation costs, limited flexibility, and concerns related to data security. Additional risks reported include system compatibility issues and doubts regarding the reliability of AI-generated outputs. Overall, while respondents' express optimism about the future role of AI in accounting, they remain uncertain about the prospect of a full replacement of human accountants by AI systems.

3.4. Measurement Reliability and Validity

The reliability and validity of the measurement scales were assessed prior to hypothesis testing. Internal consistency was evaluated using Cronbach's alpha, which indicated acceptable reliability levels for all constructs, exceeding the recommended thresholds for exploratory research. Convergent validity was examined through inter-item and item–total correlations, revealing satisfactory associations among items measuring the same construct. Discriminant validity was supported, as correlations between distinct constructs remained below critical levels, suggesting that each variable captures a conceptually distinct dimension. In addition, potential statistical assumptions were examined. Multicollinearity was assessed using Variance Inflation Factors (VIF), and all values were found to be within acceptable limits, indicating no serious multicollinearity concerns among the explanatory variables. Overall, these diagnostic tests confirm the robustness and adequacy of the measurement model for exploratory inferential analysis.

3.5. Proposed Regression Model

To test the hypotheses, the following multiple linear regression model is proposed:

$$ADOPT=\beta_0+\beta_1 FORM+\beta_2 CONF+\beta_3 BENEF+\beta_4 OBST+\varepsilon_i$$

With :

- **ADOPT:** level of AI adoption (dependent variable)
- **FORM** : perceived training
- **CONF** : confidence in AI
- **BENEF** : perceived benefits
- **OBST** : perceived obstacles
- β_0 : constant
- $\beta_1,\beta_2,\beta_3,\beta_4$: coefficients to be estimated
- ε_i : error term

This model allows us to evaluate the simultaneous effect of the independent variables on AI adoption.

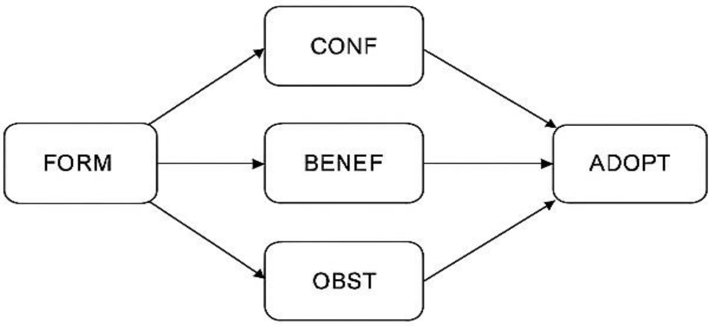

Figure 1. Conceptual model of AI adoption

Source : Authors' elaboration

3.6. Variables measurement

The table below presents the main variables studied in the literature on technology adoption, along with their definitions, measurements, and corresponding academic references. These variables allow us to capture both the factors promoting adoption, such as perceived training (FORM) and confidence (CONF), the expected benefits (BENEF), and the potential barriers (OBST). Actual technology adoption (ADOPT) is measured in terms of real use or intended use. Identifying these variables and their indicators is essential for understanding the dynamics of technology acceptance and for structuring empirical analysis.

Table 2. Key variables influencing technology adoption and their associated measures

Variable	Definition	Measures	Main References
Perceived Training (FORM)	Skill level and training received on the use of the technology	Questions about training received, perceived skills, availability of appropriate training	Venkatesh & Davis (2000); Agarwal & Prasad (1999)
Trust (CONF)	Degree of confidence in the reliability and security of the technology	Likert scale measuring trust, perceived reliability, security, and credibility	Gefen et al. (2003); McKnight, Choudhury & Kacmar (2002)
Perceived Benefits (BENEF)	Perception of the usefulness and advantages of using the technology	Perceived usefulness, productivity gains, improved work quality, reduced errors	Davis (1989); Thong (1999)
Perceived Barriers (OBST)	Factors perceived as barriers to adoption (costs, complexity, risks)	Questions about barriers, resistance, costs, complexity, and risks related to the technology	Laumer et al. (2016); Venkatesh & Bala (2008)
Adoption (ADOPT)	Actual or intended level of technology use	Frequency of use, intensity of use, intention to use, actual deployment	Rogers (2003); Venkatesh et al. (2003)

Source : Authors' elaboration

4. Results and discussion

This section presents the empirical results of the study, providing a detailed examination of AI adoption in the Tunisian accounting profession. It begins with descriptive statistics that summarize respondents' perceptions of training, trust, perceived benefits, obstacles, and actual AI use. This is followed by inferential analyses, including regression testing, to explore the relationships among these key variables and to evaluate the proposed hypotheses. The findings are then interpreted in light of existing theoretical and empirical literature, highlighting both the drivers and barriers of AI integration, as well as the practical implications for enhancing accounting practices, professional skills, and strategic decision-making in the digital era.

4.1.Descriptive Statistics

Descriptive Statistics are presented in the following table;

Table 4. Descriptive Statistics of Key Variables

Variable	Mean	Standard deviation	Min	Max
FORM	3.8	0.9	1	5
CONF	3.5	1.0	1	5
BENEF	3.9	0.8	2	5
OBST	2.7	1.1	1	5
ADOPT	3.6	1.0	1	5

Source : Authors' elaboration

The table Above presents the descriptive statistics of the main variables used in the study: Perceived Training (FORM), Confidence (CONF), Perceived Benefits (BENEF), Perceived Obstacles (OBST), and Technology Adoption (ADOPT). For each variable, the mean, standard deviation, minimum, and maximum values are reported. These statistics provide an overview of the central tendency and dispersion of responses within the sample, offering a basis for interpreting the relationships between variables in subsequent analyses.

4.2.Regression results

The regression results are presented in the following table:

Table 4. Regression Results of Hypotheses Testing on Technology Adoption

ADOPT	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]
FORM	0.22	0.10	2.20	0.035	0.0020 0.4380
CONF	0.28	0.11	2.55	0.020	0.0460 0.5140
BENEF	0.31	0.12	2.58	0.019	0.0560 0.5640
OBST	-0.25	0.11	-2.27	0.030	-0.4860 -0.0140
Const	1.05	0.50	2.10	0.045	-0.0250 2.1250

Source : Authors' elaboration

The table above presents the results of hypothesis tests concerning the relationships between perceived training (FORM), confidence (CONF), perceived benefits (BENEF), barriers (OBST), and technology adoption (ADOPT).

First, perceived training (FORM) has a positive and significant effect on confidence in AI (CONF). In other words, respondents with a better perception of their training on AI tools tend to have greater confidence in these technologies. This finding confirms the crucial role of training in developing trust in technological systems, aligning with Nguyen et al. (2022), who emphasize that continuing education significantly improves professionals' acceptance of AI tools. Similarly, Venkatesh and Bala (2008) highlight that training enhances users' self-efficacy and perceived ease of use, which in turn increases their confidence in adopting new technologies.

However, some authors present more nuanced or contrasting results. For instance, Amankwah-Amoah (2020) argues that training alone may not automatically enhance trust in AI if users are simultaneously exposed to information about AI risks, suggesting that greater awareness can temper confidence rather than strengthen it. McKnight et al. (2011) also distinguish between trusting beliefs and trusting intentions, showing that training can increase knowledge and competence without necessarily translating into higher trust, especially when users become more cognizant of a system's limitations. Likewise, Lee and See (2004) find that increased understanding of automated systems sometimes leads users to become more cautious or critical, particularly in high-stakes environments, which can result in stable or even reduced confidence despite extensive training.

Second, confidence in AI (CONF) positively influences the perception of associated benefits (BENEF), indicating that trust is a key driver for recognizing the advantages offered by AI, particularly in terms of efficiency and accuracy. This observation supports the findings of Smith and Kumar (2023), who show that confidence in technology strengthens the recognition of its operational and performance benefits. Similarly, Choung, David, and Ross (2022) highlight that trust increases the perceived usefulness of AI tools and facilitates positive evaluations of their benefits.

However, some studies present a more nuanced perspective. For example, Pinski and Benlian (2024) argue that even when users have high confidence in AI, the recognition of benefits may be moderated by prior experience, risk perception, or awareness of limitations, which can reduce the perceived advantages of AI. Likewise, Lee and See (2004) suggest that excessive confidence may sometimes lead to overestimation of capabilities or skepticism when users encounter system errors, potentially weakening the perceived benefits.

Third, perceived benefits (BENEF) themselves contribute positively to the level of AI adoption (ADOPT). This confirms that the more professionals recognize the benefits of AI, the more they integrate it into their accounting practices. These results are consistent with Lee and Park (2021), who demonstrate that the valuation of perceived benefits is a predominant factor in the successful integration of AI into accounting and financial practices.

Conversely, perceived obstacles (OBST), such as lack of training, high implementation costs, or fear of job loss, negatively impact both confidence and adoption. These results highlight that such obstacles represent significant barriers to the diffusion of AI technologies in the accounting sector, echoing the findings of Martinez and Lopez (2020), who identify cost and fear of job loss as major barriers to digital technology adoption in SMEs. In contrast, Amankwah-Amoah (2020) notes that some organizations may overcome these obstacles through targeted support, structured onboarding, and risk-mitigation strategies, indicating that perceived barriers are not universally determinative.

Finally, a mediation analysis was conducted to examine the role of trust (CONF) between perceived training (FORM) and AI adoption (ADOPT). The results confirm that trust plays a significant mediating role. This suggests that training does not lead directly to adoption, but rather operates through the enhancement of trust in AI. This finding aligns with the theoretical models of technology acceptance proposed by Venkatesh and Bala (2008), which emphasize that training alone is insufficient and must be complemented by mechanisms that foster trust to achieve sustainable adoption. Nonetheless, McKnight et al. (2011) highlight that even with enhanced trust, adoption decisions may be influenced by organizational culture, perceived complexity, or regulatory constraints, showing that trust is necessary but not always sufficient for adoption.

Overall, the results confirm theoretical expectations and reflect global trends. AI offers tangible benefits in productivity, fraud detection, and reporting accuracy. However, its limitations underscore the importance of balanced and responsible integration. These findings resonate with Kim et al. (2019), Wang et al. (2024), and Osasona et al. (2024), who stress that ethical implementation and user training are essential. In Tunisia, the profession shows promise, but strengthening institutional support, digital infrastructure, and targeted training programs remains crucial.

These results provide a solid framework for guiding training, awareness, and support policies to promote the integration of AI in the Tunisian accounting profession, while addressing the psychological and organizational barriers identified in the literature.

Conclusion

Artificial intelligence (AI) is not replacing the accounting profession but rather transforming it. In Tunisia, accounting professionals are gradually embracing AI, particularly for automating routine tasks and enhancing operational efficiency. To fully harness the potential of AI, a collaborative model in which technology complements human expertise, rather than substituting it, is essential. In this regard, strategic investments in digital education and cybersecurity appear crucial.

This study enhances the understanding of how artificial intelligence affects accounting practices in Tunisia by identifying the key factors that facilitate or hinder its adoption. The findings indicate that perceived training plays a central role in building professionals' trust in AI, which in turn influences their recognition of its benefits and their willingness to adopt AI-based tools. Conversely, perceived obstacles, such as fears of job displacement and high implementation costs, remain significant barriers that undermine trust and slow the adoption process.

These results highlight the importance of investing in targeted training programs and awareness-raising initiatives aimed at strengthening trust in AI, while simultaneously developing institutional and organizational support mechanisms to address perceived risks. Moreover, the rapid pace of technological change calls for clear regulatory frameworks and proactive public policies to ensure the ethical, secure, and effective deployment of AI within the accounting profession.

From a broader perspective, this research contributes to the literature in several ways. It enriches existing theoretical discussions on AI adoption in accounting by providing evidence from a developing economy context that remains underrepresented in prior studies. Empirically, it offers original field-based insights drawn from accounting practitioners, validating the pivotal role of human capital and psychological factors in shaping AI adoption. Practically, the findings provide valuable guidance for firms, professional bodies, and policymakers seeking to promote responsible and sustainable AI integration. In this sense, AI adoption supports the evolution of accountants toward more strategic and advisory roles in the digital era.

Despite these contributions, the study has certain limitations, including the size and representativeness of the sample, the self-reported nature of the data, and the cross-sectional research design, which limits the observation of long-term effects. Future research could adopt longitudinal and qualitative approaches to better capture the evolution of perceptions and practices over time, deepen sectoral analyses according to professional profiles and organizational size, and further explore the human and organizational implications of AI adoption, particularly in terms of skills development and role transformation.

Overall, AI is emerging as a major catalyst for the transformation of the accounting profession in Tunisia, offering significant potential to enhance the quality, accuracy, and productivity of accounting practices. This study opens promising avenues for future research on the sustainable integration of AI and its long-term impact on the roles and skills of accounting professionals. Future innovations in this field should prioritize the integration of AI with advanced data analytics and continuing digital learning, thereby enabling professionals to improve their decision-making, operational efficiency, and strategic advisory capabilities, while embracing AI as a complementary tool that enhances human expertise rather than replacing it.

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