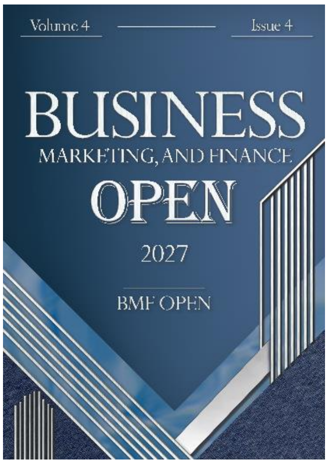
Analysis of Factors Affecting Professional Accountants' Resistance to the Implementation of Artificial Intelligence and Its Consequences for Financial Digital Transformation

Hossein Keikhaei [1,*]

[1] Department of Accounting, Faculty of Management and Accounting, University of Tehran, Tehran, Iran;

* Correspondence: hosseinkeikhaei@ut.ac.ir



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Abstract: This study aimed to analyze the factors affecting professional accountants' resistance to the implementation of artificial intelligence and to examine the consequences of this resistance for financial digital transformation. This applied quantitative study was conducted using a descriptive-correlational design with a structural equation modeling approach. The statistical population consisted of professional accountants working in Tehran in private companies, audit firms, tax and financial consulting institutions, and financial departments of industrial, commercial, and service organizations. A total of 384 professional accountants were selected through purposive sampling based on inclusion criteria, including relevant academic background, at least three years of professional experience, and direct involvement in accounting, auditing, financial reporting, taxation, or financial analysis processes. Data were collected using a structured questionnaire measuring perceived job insecurity, fear of skill obsolescence, perceived complexity of artificial intelligence systems, lack of trust in algorithmic outputs, data security and ethical responsibility concerns, perceived threat to professional judgment, insufficient organizational support and training, overall resistance to artificial intelligence implementation, and impairment of financial digital transformation. Data were analyzed using descriptive statistics, Pearson correlation coefficients, confirmatory factor analysis, and structural equation modeling. The inferential results showed that perceived job insecurity ($\beta = 0.18$, $p < 0.001$), fear of skill obsolescence ($\beta = 0.21$, $p < 0.001$), perceived AI complexity ($\beta = 0.14$, $p = 0.001$), lack of trust in algorithmic outputs ($\beta = 0.16$, $p < 0.001$), data security and ethical responsibility concerns ($\beta = 0.10$, $p = 0.021$), perceived threat to professional judgment ($\beta = 0.09$, $p = 0.039$), and insufficient organizational support and training ($\beta = 0.24$, $p < 0.001$) significantly predicted resistance to AI implementation. These variables explained 62% of the variance in resistance. Resistance to AI implementation significantly predicted impairment of financial digital transformation ($\beta = 0.68$, $p < 0.001$), explaining 46% of its variance. The findings indicate that resistance to artificial intelligence among professional accountants is shaped by employment, skill, technological, ethical, and organizational concerns and can substantially weaken financial digital transformation. Therefore, successful AI implementation in accounting requires systematic training, transparent communication, ethical governance, role redesign, and organizational support.

Keywords: Artificial intelligence; professional accountants; resistance to change; financial digital transformation; accounting technology; structural equation modeling.

1. Introduction

Artificial intelligence has become one of the most influential drivers of digital transformation across contemporary organizations, reshaping how professional knowledge is produced, processed, interpreted, and applied in decision-making. In financial and accounting environments, artificial intelligence is no longer limited to experimental automation or isolated software functions; rather, it is increasingly embedded in accounting information systems, audit analytics, fraud detection tools, predictive financial models, intelligent reporting platforms, tax compliance systems, risk assessment mechanisms, and management accounting dashboards. The broader literature on digital transformation indicates that AI-based technologies can improve service efficiency, analytical accuracy, real-time monitoring, personalization, and decision quality when they are implemented within coherent organizational and professional frameworks [1-3]. However, the transition from conventional digitalization to AI-driven transformation is not merely a technical process. It also involves changes in professional roles, work identity, organizational routines, ethical responsibility, knowledge authority, and the relationship between human judgment and algorithmic decision-making. For this reason, the implementation of artificial intelligence in accounting should be examined not only as a technological innovation, but also as a socio-professional transformation that may generate uncertainty, resistance, and adaptation challenges among professional accountants.

Accounting has historically been shaped by technological change. The shift from manual bookkeeping to computerized accounting, the development of enterprise resource planning systems, the diffusion of cloud-based financial platforms, and the use of integrated reporting systems have all changed the scope and speed of accounting work. Recent studies have emphasized that digital technologies are transforming accounting and finance by enabling automation, data integration, real-time financial reporting, and more analytical forms of financial decision-making [4, 5]. In the digital economy, management accounting is also being redefined through data-driven planning, performance evaluation, cost management, and strategic decision support [6]. Artificial intelligence intensifies this transformation because it does not only accelerate existing accounting tasks, but also performs pattern recognition, anomaly detection, predictive modeling, document interpretation, and decision-support functions that were previously dependent on human expertise. In banking and financial systems, AI has already been associated with changes in customer analytics, risk management, credit evaluation, fraud detection, and operational efficiency [7]. Within accounting and auditing, technological disruption has been particularly visible in the emergence of regulatory technology, AI-based optical character recognition, automated compliance systems, and intelligent audit analytics [8]. These developments suggest that professional accountants are entering a period in which technical accounting knowledge must be combined with digital literacy, analytical reasoning, and the ability to work alongside intelligent systems.

Despite the potential benefits of artificial intelligence, its implementation in accounting and finance may face significant resistance from professional accountants. Resistance to AI can emerge when professionals perceive new systems as threats to their employment security, professional identity, autonomy, judgment, or established competencies. The literature on skill transformation in the workplace shows that AI adoption often produces concerns about reskilling, upskilling, job redesign, and the future relevance of existing professional capabilities [9, 10]. In accounting, these concerns may be especially salient because many routine and rule-based tasks, such as invoice processing, reconciliation, classification, compliance checking, and transaction monitoring, are highly susceptible to automation. While artificial intelligence may create opportunities for accountants to move toward advisory, analytical, strategic, and interpretive roles, this transition requires professional development and organizational support. Without adequate preparation, accountants may interpret AI not as a tool that expands their professional capacity, but as a mechanism that reduces their occupational value. Similar concerns have been identified in other sectors where AI changes the distribution of work, responsibility, and required competencies, including public health education, healthcare services, libraries, and small businesses [11-14]. Therefore, resistance among accountants should be understood as a rational response to perceived uncertainty rather than simply as unwillingness to adopt technology.

One of the central sources of resistance is fear of skill obsolescence. Professional accountants invest years in acquiring technical knowledge related to accounting standards, taxation, auditing procedures, financial reporting, internal control, and managerial decision support. When artificial intelligence systems are introduced into these domains, accountants may fear that their accumulated expertise will become less valuable or that future accounting work will be dominated by data scientists, system designers, and algorithmic platforms. The literature on AI skills emphasizes that successful digital transformation requires systematic upskilling and reskilling strategies, because professionals need to understand both the opportunities and limitations of AI-supported work [9, 10]. This concern is not limited to accounting. University professors, healthcare workers, public relations professionals, and public health educators have also shown that acceptance of AI depends partly on perceived competence, perceived usefulness, readiness for change, and the availability of institutional support [11, 15-17]. For accountants, insufficient training may intensify resistance because AI implementation changes not only the tools used in work but also the criteria by which competence and professional authority are evaluated. Accountants may therefore require more than technical instruction; they need clear role redesign, professional reassurance, and opportunities to reinterpret their expertise in relation to AI-assisted financial work.

Trust is another essential factor in the implementation of artificial intelligence in accounting. Accounting and auditing depend heavily on reliability, verifiability, accountability, professional skepticism, and evidence-based judgment. If accountants do not trust algorithmic outputs, they may resist using AI-generated recommendations in financial reporting, audit testing, risk assessment, or fraud detection. The issue of trust is particularly important because AI systems may operate through complex models whose logic is not always transparent to users. In healthcare, education, cytopathology, medical imaging, and dentistry, researchers have emphasized that AI adoption is shaped by concerns regarding accuracy, explainability, professional oversight, communication, and the preservation of human responsibility [18-21]. Similar concerns apply to accounting because financial decisions have legal, regulatory, and economic consequences. When an AI system classifies transactions, flags anomalies, predicts cash flow, or assesses audit risk, accountants may question who is responsible for errors, how algorithmic conclusions can be justified, and whether the system's outputs can withstand professional or legal scrutiny. Therefore, resistance to AI in accounting is closely linked to the perceived transparency, reliability, and auditability of intelligent systems.

Ethical and legal concerns also play a fundamental role in accountants' resistance to artificial intelligence. Accounting information is highly sensitive because it contains confidential organizational data, financial statements, tax records, payroll information, supplier and customer data, strategic budgets, and internal control documentation. The use of AI in such contexts raises questions about data privacy, cybersecurity, unauthorized access, algorithmic bias, professional liability, and compliance with legal and ethical standards. Studies on AI implementation in healthcare have repeatedly emphasized that adoption challenges are closely tied to privacy, ethics, responsibility, regulation, and institutional governance [22-24]. These concerns are transferable to financial professions, where the consequences of data misuse or algorithmic error may include financial loss, regulatory penalties, audit failure, reputational damage, and erosion of stakeholder trust. In cybersecurity-related discussions, human-in-the-loop approaches have been presented as essential for balancing automation with oversight, accountability, and risk control [25]. For accountants, resistance may therefore reflect the perception that AI systems should not replace professional judgment without adequate ethical safeguards, data governance mechanisms, and accountability structures.

Organizational support is another determinant of accountants' willingness to engage with artificial intelligence. The implementation of AI requires strategic planning, managerial commitment, training investment, user participation, process redesign, technical infrastructure, and a culture of learning. Without these conditions, AI systems may be perceived as imposed technologies rather than collaborative tools. Studies from different fields have shown that institutional readiness, leadership support, workforce preparation, and implementation context strongly influence AI adoption [3, 26, 27]. In business and pricing functions, sustainable implementation of AI-supported systems requires assessment models that consider organizational capabilities, operational alignment, and long-term value creation rather than purely technical performance [28]. In engineering and other applied domains, informed machine learning has also been discussed as a means of integrating technical modeling with domain knowledge, which highlights the importance of collaboration between AI systems and professional expertise [29]. In the accounting context, this means that accountants are more likely to accept AI when they are involved in implementation, trained in system logic, assured about professional responsibilities, and supported in adapting their work practices. Conversely, when AI is introduced without consultation, explanation, or training, resistance becomes more likely.

The perceived threat to professional judgment is particularly important in accounting. Accounting is not simply a mechanical process of recording transactions; it involves interpretation, estimation, classification, materiality judgment, risk assessment, ethical reasoning, and communication with stakeholders. AI can support these processes, but it may also be perceived as reducing the accountant's interpretive authority. The literature on knowledge, ethics, and generative AI suggests that AI challenges traditional understandings of expertise, authorship, responsibility, and knowledge production [30]. In libraries and information services, similar questions have emerged regarding how AI affects professional roles, service quality, and human expertise [13, 31]. For accountants, the central concern is whether AI will enhance professional judgment or gradually displace it. In external auditing, ongoing debates have shown that AI can improve audit quality through better data analysis and anomaly detection, but it also raises concerns about professional skepticism, accountability, and the interpretation of audit evidence [32]. Likewise, AI-driven fraud detection may strengthen financial control systems, but it also requires careful attention to model reliability, false positives, explainability, and the role of professional interpretation [33]. Resistance may therefore emerge when accountants believe that AI threatens the human judgment that forms the foundation of professional accounting responsibility.

The consequences of resistance are significant because resistance can slow or weaken financial digital transformation. If accountants hesitate to use AI-based tools, organizations may experience delays in adopting intelligent financial systems, weak integration between accounting platforms and analytical technologies, limited use of predictive financial analytics, reduced efficiency in reporting, and insufficient exploitation of real-time financial data. In sectors such as healthcare, agriculture, construction, and public services, AI has been associated with possibilities for improved decision-making, resource optimization, sustainability, service quality, and operational effectiveness when implementation is responsible and context-sensitive [1, 34-36]. The accounting profession faces a similar challenge: AI can support sustainable financial transformation only when professionals adopt it as part of their work. In international accounting systems, information technologies have already been shown to affect accounting integration, reporting, and enterprise-level financial processes [37]. However, technological investment alone is not sufficient. If professional users distrust the systems, fear role displacement, or lack the skills to use AI effectively, digital transformation may remain superficial, fragmented, and underutilized.

Accordingly, the study of accountants' resistance to artificial intelligence is necessary because it connects individual attitudes, professional identity, technological readiness, ethical concerns, organizational support, and digital transformation outcomes within one analytical framework. Existing studies across different sectors have clarified that AI adoption depends on perceived usefulness, trust, ethics, skills, governance, and institutional readiness, but accounting requires a more specific analysis because accountants operate within environments characterized by regulatory accountability, financial confidentiality, professional judgment, and high consequences for error [2, 12, 16, 26]. Although AI has the potential to transform accounting from routine processing toward strategic financial intelligence, the realization of this potential depends on whether accountants accept, understand, and professionally integrate these systems. Therefore, identifying the factors that intensify resistance and explaining how this resistance affects financial digital transformation can provide practical guidance for organizations, policymakers, accounting educators, technology developers, and professional bodies seeking to implement AI responsibly and effectively.

The aim of this study was to analyze the factors affecting professional accountants' resistance to the implementation of artificial intelligence and to examine the consequences of this resistance for financial digital transformation.

2. Methodology

This study was conducted using an applied, quantitative, descriptive-correlational design with a structural equation modeling approach. The purpose of the study was to analyze the factors affecting professional accountants' resistance to the implementation of artificial intelligence and to examine the consequences of this resistance for financial digital transformation. The statistical population consisted of professional accountants working in Tehran, including accountants employed in private companies, audit firms, financial and tax consulting institutions, industrial and commercial organizations, and financial departments of service organizations. Since the study focused on professional resistance to artificial intelligence in accounting practice, participants were required to have at least a bachelor's degree in accounting, finance, auditing, or a related field, at least three years of professional work experience, and direct involvement in accounting, auditing, financial reporting, budgeting, taxation, internal control, or financial analysis processes. Accountants who had no practical experience with computerized accounting systems, enterprise resource planning systems, digital financial platforms, or AI-related accounting tools were not included in the study. The sample consisted of 384 professional accountants from Tehran. This sample size was considered adequate for structural equation modeling and was determined based on the size of the target population, the number of observed variables, and the need to obtain stable parameter estimates in the proposed conceptual model. Participants were selected through a purposive sampling method, because the research required respondents who had sufficient professional knowledge of accounting processes and adequate familiarity with digital technologies used in financial work. To increase the representativeness of the sample, accountants were recruited from different organizational settings, including audit firms, corporate accounting units, financial management departments, tax service offices, and accounting service companies. Data were collected after explaining the purpose of the research to the participants and ensuring them that their responses would remain confidential and would be used only for academic purposes. Participation in the study was voluntary, and only fully completed questionnaires were entered into the final analysis.

Data were collected using a structured questionnaire composed of three main sections. The first section included demographic and occupational information, such as age, gender, educational level, field of study, years of professional experience, current job position, type of organization, previous experience with accounting software, familiarity with artificial intelligence applications in accounting, and perceived level of digital readiness. These variables were included to describe the characteristics of the respondents and to control for possible background differences that could influence attitudes toward artificial intelligence implementation. The demographic and occupational items were designed to capture the professional context of accountants in Tehran, because resistance to artificial intelligence may vary according to work experience, organizational role, exposure to digital systems, and the extent to which accounting tasks are already supported by technology.

The second section measured factors affecting professional accountants' resistance to the implementation of artificial intelligence. This part of the questionnaire was developed based on the theoretical foundations of technology acceptance, innovation resistance, organizational change, and digital transformation in financial professions. The scale assessed several dimensions of resistance, including perceived job insecurity, fear of skill obsolescence, perceived complexity of artificial intelligence systems, lack of trust in algorithmic outputs, concerns about data security and professional responsibility, perceived reduction of professional judgment, insufficient organizational support, lack of training, uncertainty about ethical and legal consequences, and negative attitude toward technological change. Items were scored on a five-point Likert scale ranging from strongly disagree to strongly agree. Higher scores indicated a higher level of resistance to artificial intelligence implementation. The initial items were reviewed by experts in accounting, auditing, financial management, information systems, and research methodology to evaluate content validity, clarity, relevance, and conceptual coverage. After expert review, ambiguous or overlapping items were revised or removed. The reliability of the scale was evaluated using internal consistency coefficients, and its construct validity was examined through confirmatory factor analysis before testing the structural model.

The third section measured the consequences of accountants' resistance to artificial intelligence for financial digital transformation. This section assessed the extent to which resistance to artificial intelligence could affect the progress, quality, and effectiveness of digital transformation in financial functions. The main dimensions included delay in adopting digital financial systems, reduced integration of artificial intelligence into accounting and auditing processes, decreased quality of data-driven decision-making, lower efficiency in financial reporting, limited use of predictive analytics, weakness in real-time financial monitoring, reduced organizational agility, and disruption in the development of intelligent financial control systems. Items were scored on a five-point Likert scale from strongly disagree to strongly agree. Higher scores reflected stronger negative consequences of resistance for financial digital transformation. The scale was designed to examine digital transformation not merely as the use of software, but as a broader process involving automation, intelligent analysis, data integration, predictive decision-making, and redesign of financial workflows. The face and content validity of this section were assessed by a panel of specialists, and the reliability and construct validity of the instrument were evaluated statistically before hypothesis testing. The final questionnaire was administered in person and electronically, depending on participants' accessibility and organizational conditions.

Data analysis was performed using descriptive statistics and structural equation modeling. In the first stage, the completed questionnaires were screened to identify missing data, incomplete responses, outliers, and response patterns that could reduce the quality of analysis. After data screening, descriptive statistics, including frequency, percentage, mean, standard deviation, skewness, and kurtosis, were used to describe the demographic characteristics of the participants and the distribution of the main research variables. The normality of the data was examined through skewness and kurtosis indices, and the adequacy of the dataset for multivariate analysis was assessed before estimating the measurement and structural models. Reliability was evaluated using Cronbach's alpha and composite reliability, and convergent validity was assessed through factor loadings and average variance extracted. Discriminant validity was examined by comparing shared variance among constructs and by evaluating the distinctiveness of the latent variables included in the model.

In the second stage, confirmatory factor analysis was used to assess the measurement model and to determine whether the observed items adequately represented the latent constructs of resistance to artificial intelligence and financial digital transformation. Items with weak factor loadings or insufficient theoretical relevance were removed only when their removal improved the validity and interpretability of the model. After confirming the adequacy of the measurement model, the structural model was tested to examine the direct effects of resistance-related factors on accountants' overall resistance to artificial intelligence and the effect of this resistance on financial digital transformation. The structural model also made it possible to identify the relative importance of psychological, professional, technological, and organizational factors in explaining resistance to artificial intelligence implementation. Model fit and explanatory power were evaluated using appropriate indices, including path coefficients, coefficient of determination, predictive relevance, and overall model quality indicators. The significance of the structural paths was tested using bootstrapping procedures with repeated resampling. The level of statistical significance was set at 0.05.

3. Findings and Results

The final analysis was conducted on data obtained from 384 professional accountants working in Tehran. The participants included 218 men and 166 women, representing 56.8% and 43.2% of the sample, respectively. The mean age of the participants was 37.42 years with a standard deviation of 7.86 years, indicating that the sample mainly consisted of accountants in the middle stage of their professional careers. In terms of age distribution, 58 participants were between 25 and 30 years old, 188 participants were between 31 and 40 years old, 109 participants were between 41 and 50 years old, and 29 participants were older than 50 years. Regarding educational level, 201 participants held a bachelor's degree, 156 held a master's degree, and 27 held a doctoral degree in accounting, finance, auditing, management, or related fields. With regard to professional experience, 74 participants had between 3 and 5 years of experience, 132 participants had between 6 and 10 years of experience, 98 participants had between 11 and 15 years of experience, and 80 participants had more than 15 years of professional experience. The organizational distribution of the respondents showed that 146 participants were employed in private companies, 92 worked in audit firms, 73 were employed in tax, accounting, or financial consulting institutions, and 73 worked in financial departments of industrial, commercial, or service organizations. In terms of familiarity with artificial intelligence applications in accounting and finance, 92 participants reported low familiarity, 203 reported moderate familiarity, and 89 reported high familiarity. Overall, the demographic and occupational profile of the sample indicated that the respondents had sufficient educational background, professional exposure, and practical experience to provide meaningful responses regarding artificial intelligence implementation, professional resistance, and financial digital transformation.

Table 1. Descriptive Statistics, Normality Indices, Reliability, and Convergent Validity of the Main Research Constructs

Construct	Items	Mean	SD	Skewness	Kurtosis	Cronbach's Alpha	Composite Reliability	AVE
Perceived job insecurity	5	3.78	0.72	-0.41	0.28	0.86	0.89	0.62
Fear of skill obsolescence	5	3.91	0.68	-0.53	0.47	0.88	0.91	0.67
Perceived complexity of artificial intelligence systems	5	3.64	0.75	-0.28	0.11	0.84	0.87	0.58
Lack of trust in algorithmic outputs	6	3.70	0.71	-0.34	0.22	0.89	0.92	0.65
Data security, ethical, and professional responsibility concerns	6	3.83	0.69	-0.46	0.36	0.90	0.92	0.66
Perceived threat to professional judgment	5	3.59	0.77	-0.25	-0.07	0.85	0.88	0.60
Insufficient organizational support and training	5	3.87	0.74	-0.49	0.43	0.87	0.90	0.64
Overall resistance to artificial intelligence implementation	7	3.76	0.66	-0.38	0.31	0.91	0.93	0.66
Impairment of financial digital transformation	8	3.68	0.70	-0.32	0.26	0.92	0.94	0.68

The descriptive results in Table 1 show that all research constructs had mean scores above the theoretical midpoint of the five-point scale, indicating that resistance-related perceptions were generally present among professional accountants in Tehran. The highest mean score was related to fear of skill obsolescence, suggesting that many accountants were concerned that the implementation of artificial intelligence could reduce the value of their current professional knowledge and technical competencies. Insufficient organizational support and training also had a high mean score, showing that lack of preparation, inadequate training programs, and weak organizational communication may be important sources of resistance. Data security, ethical, and professional responsibility concerns also received a relatively high mean, which indicates that accountants were not only concerned about job replacement but also about accountability, confidentiality, auditability, and the reliability of financial decisions supported by artificial intelligence. The skewness and kurtosis values were within the acceptable range, suggesting that the distribution of the variables did not seriously violate normality assumptions. Reliability coefficients were also satisfactory, as all Cronbach's alpha values were above 0.84 and all composite reliability values were above 0.87. The average variance extracted values were all above 0.50, confirming acceptable convergent validity. Therefore, the measurement properties of the constructs were considered adequate for subsequent correlation and structural equation modeling analyses.

Table 2. Pearson Correlation Matrix among the Main Research Constructs

Construct	1	2	3	4	5	6	7	8	9
1. Perceived job insecurity	1								
2. Fear of skill obsolescence	0.57**	1							
3. Perceived AI complexity	0.46**	0.49**	1						
4. Lack of trust in algorithmic outputs	0.44**	0.51**	0.53**	1					
5. Data security, ethical, and responsibility concerns	0.42**	0.48**	0.45**	0.56**	1				
6. Threat to professional judgment	0.39**	0.43**	0.41**	0.50**	0.47**	1			
7. Insufficient organizational support and training	0.52**	0.55**	0.50**	0.48**	0.46**	0.44**	1		
8. Overall resistance to AI implementation	0.61**	0.64**	0.55**	0.58**	0.53**	0.49**	0.62**	1	
9. Impairment of financial digital transformation	0.50**	0.56**	0.47**	0.52**	0.49**	0.45**	0.54**	0.68**	1

**$p < 0.01$.

The correlation results in Table 2 indicate that all dimensions related to resistance to artificial intelligence had positive and statistically significant relationships with overall resistance to artificial intelligence implementation. The strongest correlations with overall resistance were observed for fear of skill obsolescence, insufficient organizational support and training, and perceived job insecurity. This finding suggests that resistance among professional accountants is strongly connected to concerns about losing professional relevance, not receiving adequate institutional preparation, and perceiving artificial intelligence as a threat to employment security. Lack of trust in algorithmic outputs and perceived complexity of artificial intelligence systems were also moderately to strongly correlated with overall resistance, indicating that technical uncertainty and doubts about the reliability of automated financial judgments can intensify negative attitudes toward artificial intelligence. In addition, overall resistance to artificial intelligence had a strong positive correlation with impairment of financial digital transformation. This means that the more accountants resisted artificial intelligence implementation, the more likely they were to report delays, inefficiencies, weak integration of digital systems, and limited progress in intelligent financial transformation. The pattern of correlations supports the conceptual assumption that professional, psychological, technological, and organizational factors are interconnected and jointly contribute to resistance behavior in accounting environments.

Table 3. Structural Model Results for Factors Affecting Professional Accountants' Resistance to Artificial Intelligence Implementation

Predictor Variable	Standardized Beta	Unstandardized Coefficient	SE	t-value	p-value	Effect Size f^2	Result
Perceived job insecurity → Resistance to AI implementation	0.18	0.17	0.04	4.25	<0.001	0.052	Supported
Fear of skill obsolescence → Resistance to AI implementation	0.21	0.20	0.04	5.12	<0.001	0.071	Supported
Perceived AI complexity → Resistance to AI implementation	0.14	0.12	0.04	3.30	0.001	0.035	Supported
Lack of trust in algorithmic outputs → Resistance to AI implementation	0.16	0.15	0.04	3.91	<0.001	0.046	Supported
Data security, ethical, and responsibility concerns → Resistance to AI implementation	0.10	0.09	0.04	2.31	0.021	0.019	Supported
Threat to professional judgment → Resistance to AI implementation	0.09	0.08	0.04	2.06	0.039	0.015	Supported
Insufficient organizational support and training → Resistance to AI implementation	0.24	0.22	0.04	5.72	<0.001	0.086	Supported

Model explanatory power: $R^2 = 0.62$.

The structural model results presented in Table 3 show that all proposed predictors had statistically significant effects on professional accountants' resistance to artificial intelligence implementation. Among the predictors, insufficient organizational support and training had the strongest effect on resistance, indicating that accountants were more likely to resist artificial intelligence when they perceived that their organizations had not provided adequate training, clear implementation plans, technical support, or participatory change-management processes. Fear of skill obsolescence was the second strongest predictor, showing that accountants who believed their current competencies could become outdated in an AI-based financial environment were more likely to develop resistant attitudes. Perceived job insecurity also had a significant positive effect, meaning that the perceived possibility of replacement, role reduction, or decreased demand for traditional accounting tasks increased resistance to artificial intelligence. Lack of trust in algorithmic outputs and perceived complexity of artificial intelligence systems also significantly predicted resistance, suggesting that accountants may oppose AI implementation when they do not understand how the systems work or when they doubt the accuracy, transparency, and professional defensibility of AI-generated results. Data security, ethical, and professional responsibility concerns, as well as perceived threat to professional judgment, had smaller but still significant effects. These results show that resistance is not caused by a single factor, but rather by a combination of employment-related anxiety, skill-related uncertainty, technological complexity, trust concerns, ethical responsibility, and inadequate organizational preparation. The coefficient of determination showed that the predictors explained 62% of the variance in resistance to artificial intelligence implementation, which indicates strong explanatory power for the proposed model.

Table 4. Effects of Resistance to Artificial Intelligence Implementation on Financial Digital Transformation Outcomes

Outcome Variable	Standardized Beta	Unstandardized Coefficient	SE	t-value	p-value	R^2
Resistance to AI implementation → Delay in adopting intelligent financial systems	0.62	0.66	0.05	14.20	<0.001	0.38
Resistance to AI implementation → Reduced integration of AI into accounting and auditing processes	0.58	0.61	0.05	12.84	<0.001	0.34
Resistance to AI implementation → Lower quality of data-driven financial decision-making	0.54	0.57	0.05	11.76	<0.001	0.29
Resistance to AI implementation → Reduced efficiency of financial reporting processes	0.49	0.51	0.05	10.42	<0.001	0.24
Resistance to AI implementation → Limited use of predictive financial analytics	0.57	0.60	0.05	12.51	<0.001	0.32
Resistance to AI implementation → Weakness in real-time financial monitoring	0.51	0.54	0.05	10.98	<0.001	0.26
Resistance to AI implementation → Reduced organizational agility in financial transformation	0.47	0.49	0.05	9.86	<0.001	0.22
Resistance to AI implementation → Overall impairment of financial digital transformation	0.68	0.72	0.04	16.88	<0.001	0.46

Model fit indices: $\chi^2/df = 2.31$, CFI = 0.934, TLI = 0.921, IFI = 0.935, RMSEA = 0.058, SRMR = 0.049.

The results in Table 4 demonstrate that resistance to artificial intelligence implementation had a significant and positive effect on all negative outcomes related to financial digital transformation. The strongest effect was observed for the overall impairment of financial digital transformation, indicating that resistance among professional accountants can meaningfully weaken the broader transformation of financial systems. Resistance had a particularly strong effect on delaying the adoption of intelligent financial systems, suggesting that when accountants are hesitant, skeptical, or professionally threatened by artificial intelligence, organizations may experience slower implementation of AI-based accounting platforms, automated reporting systems, intelligent audit tools, and predictive financial technologies. Resistance also significantly reduced the integration of artificial intelligence into accounting and auditing processes, showing that even when AI tools are formally introduced, their effective use may remain limited if accountants do not accept them as reliable and professionally useful. The results further showed that resistance weakened the quality of data-driven financial decision-making, reduced the efficiency of financial reporting processes, limited the use of predictive financial analytics, weakened real-time financial monitoring, and reduced organizational agility in financial transformation. The model fit indices were within acceptable ranges, confirming that the proposed structural model had a satisfactory fit with the observed data. These findings support the conclusion that accountants' resistance to artificial intelligence is not merely an individual attitude, but a structural barrier that can delay and weaken digital transformation in financial functions.

Table 5. Direct, Indirect, and Total Effects in the Final Structural Model

Path	Direct Effect	Indirect Effect	Total Effect	Bootstrap SE	95% Confidence Interval	p-value

Perceived job insecurity → Resistance to AI implementation → Financial digital transformation impairment	0.18	0.12	0.30	0.035	0.061 to 0.191	<0.001
Fear of skill obsolescence → Resistance to AI implementation → Financial digital transformation impairment	0.21	0.14	0.35	0.038	0.075 to 0.216	<0.001
Perceived AI complexity → Resistance to AI implementation → Financial digital transformation impairment	0.14	0.10	0.24	0.031	0.041 to 0.164	0.002
Lack of trust in algorithmic outputs → Resistance to AI implementation → Financial digital transformation impairment	0.16	0.11	0.27	0.033	0.052 to 0.179	<0.001
Data security, ethical, and responsibility concerns → Resistance to AI implementation → Financial digital transformation impairment	0.10	0.07	0.17	0.028	0.018 to 0.126	0.018
Threat to professional judgment → Resistance to AI implementation → Financial digital transformation impairment	0.09	0.06	0.15	0.027	0.011 to 0.118	0.034
Insufficient organizational support and training → Resistance to AI implementation → Financial digital transformation impairment	0.24	0.16	0.40	0.041	0.087 to 0.239	<0.001

The mediation results presented in Table 5 show that resistance to artificial intelligence implementation played a meaningful mediating role in the relationship between resistance-related antecedents and impairment of financial digital transformation. Insufficient organizational support and training had the largest total effect on financial digital transformation impairment through resistance to artificial intelligence, which means that weak organizational preparation not only directly intensifies resistance but also indirectly obstructs digital transformation by reducing accountants' willingness to engage with intelligent financial systems. Fear of skill obsolescence also had a strong total effect, indicating that accountants' concerns about losing professional relevance can become an important psychological mechanism through which AI implementation is slowed or weakened. Perceived job insecurity, lack of trust in algorithmic outputs, and perceived complexity of artificial intelligence systems also had significant indirect effects through resistance. These findings suggest that the consequences of resistance are cumulative: when accountants feel professionally insecure, inadequately trained, technically uncertain, or distrustful of algorithmic outputs, their resistance increases, and this resistance subsequently weakens the quality and speed of financial digital transformation. The confidence intervals for all indirect effects did not include zero, confirming the statistical significance of the mediation paths. Therefore, the final model shows that resistance to artificial intelligence is a central explanatory mechanism linking professional, technological, ethical, and organizational concerns to the impairment of digital transformation in financial systems.

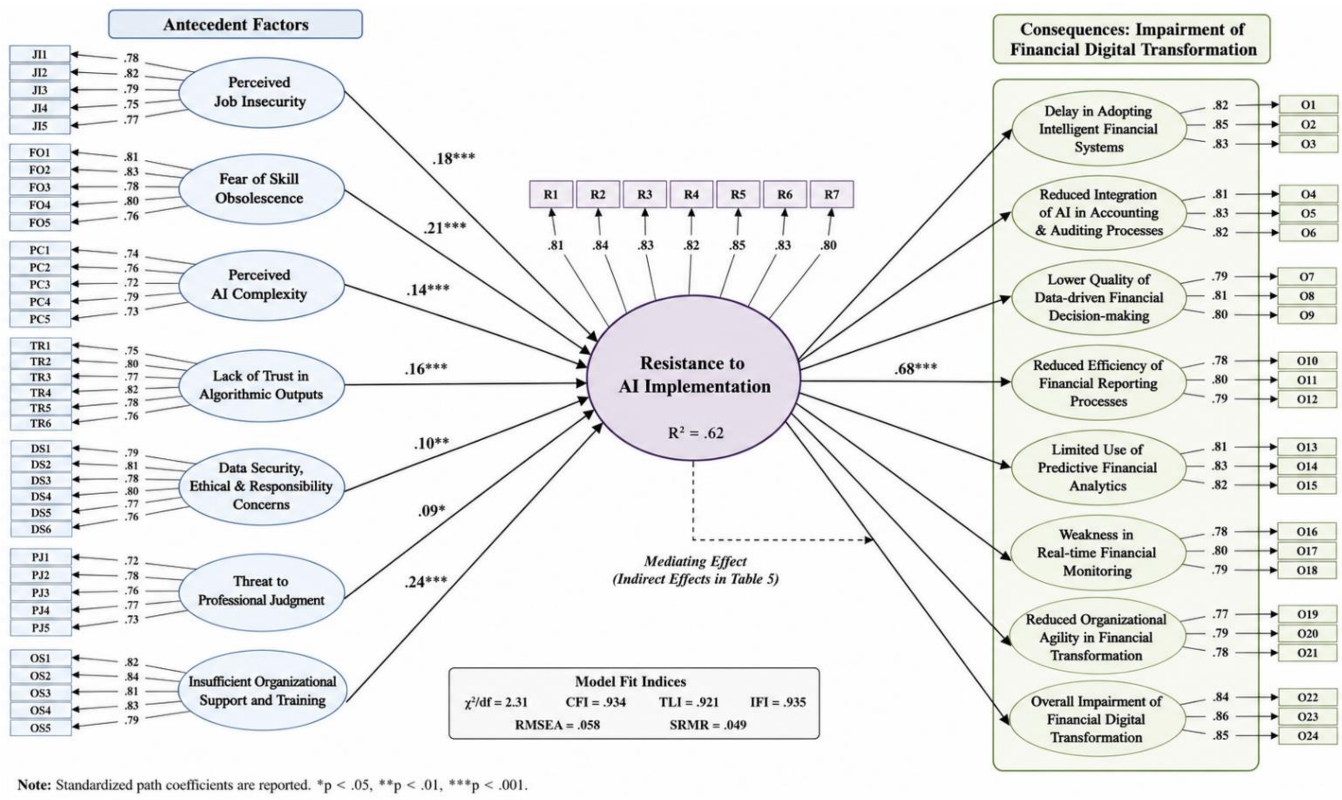

Figure 1. Final structural model of factors affecting professional accountants' resistance to artificial intelligence implementation and its consequences for financial digital transformation.

The final structural model illustrates the integrated pattern of relationships among the main variables of the study. In this model, perceived job insecurity, fear of skill obsolescence, perceived complexity of artificial intelligence systems, lack of trust in algorithmic outputs, data security and ethical responsibility concerns, perceived threat to professional judgment, and insufficient organizational support and training were positioned as antecedents of professional accountants' resistance to artificial intelligence implementation. Resistance to artificial intelligence was positioned as the central mediating construct and as the immediate predictor of impairment in financial digital transformation. The strongest path leading to resistance was from insufficient organizational support and training, followed by fear of skill obsolescence and perceived job insecurity. The strongest outcome path was from resistance to artificial intelligence implementation toward overall impairment of financial digital transformation. This pattern indicates that the successful implementation of artificial intelligence in accounting cannot be achieved only through technological investment. Instead, it requires systematic attention to professional learning, role redesign, algorithmic transparency, ethical assurance, data governance, and organizational change management. The final model therefore confirms that accountants' resistance is both an attitudinal response to perceived professional and technological threats and a practical barrier to the effective digital transformation of financial processes.

4. Discussion and Conclusion

The findings of the present study showed that professional accountants' resistance to the implementation of artificial intelligence was a multidimensional phenomenon shaped by professional, psychological, technological, ethical, and organizational factors. The descriptive results indicated that all resistance-related constructs were above the theoretical midpoint, suggesting that accountants in Tehran did not view artificial intelligence merely as a neutral technological tool, but as a transformative force with direct implications for their professional roles, competencies, responsibilities, and future position in financial systems. Among the antecedent factors, fear of skill obsolescence, insufficient organizational support and training, data security and ethical responsibility concerns, and perceived job insecurity obtained relatively high mean scores. This pattern indicates that accountants' resistance is not simply a matter of negative attitude toward technology; rather, it reflects uncertainty about how AI will redefine accounting expertise, how organizations will support professionals during transition, and how responsibility will be distributed when algorithmic systems become involved in financial judgment. This finding is consistent with the broader AI-adoption literature, which emphasizes that the implementation of AI produces not only operational opportunities but also workforce anxieties, professional identity concerns, and institutional readiness challenges [9, 10, 26]. In this respect, the results support the argument that AI-driven transformation in accounting should be interpreted as a socio-technical process rather than a purely technical modernization project.

The correlation findings demonstrated that all antecedent variables had positive and significant relationships with overall resistance to artificial intelligence implementation. The strongest correlations were observed between resistance and fear of skill obsolescence, insufficient organizational support and training, and perceived job insecurity. This result suggests that resistance among accountants becomes more intense when they believe that artificial intelligence threatens their professional relevance, reduces the value of their existing skills, or is introduced without adequate organizational preparation. These findings align with studies showing that skill transformation is one of the most important consequences of AI adoption in contemporary workplaces [9]. Similarly, research on upskilling and reskilling has emphasized that professionals are more likely to accept AI when they can clearly see how their existing knowledge will be renewed rather than replaced [10]. In the accounting context, this is especially important because many traditional functions, such as transaction classification, reconciliation, compliance checking, document processing, and routine reporting, can be automated through intelligent systems. Therefore, accountants may resist AI when they perceive it as a substitute for professional labor rather than as an extension of analytical capacity. This interpretation is consistent with studies in other professional fields showing that AI acceptance depends on perceived competence, institutional training, and confidence in future employability [11, 15, 17].

The structural model further showed that insufficient organizational support and training was the strongest predictor of resistance to artificial intelligence implementation. This finding indicates that accountants' resistance is strongly influenced by the extent to which organizations provide clear implementation strategies, participatory decision-making, technical training, managerial communication, and post-adoption support. When AI systems are introduced without explaining their purpose, limits, benefits, and implications for professional responsibilities, accountants may experience uncertainty and interpret the technology as an imposed threat. This result is supported by studies showing that institutional readiness and organizational context play decisive roles in AI implementation across sectors [3, 26, 27]. In healthcare, for instance, implementation barriers often arise not because professionals reject innovation itself, but because organizations lack sufficient infrastructure, governance, training, and integration mechanisms [12, 16]. The same logic applies to financial digital transformation. Artificial intelligence in accounting requires more than software installation; it requires redesign of workflows, clarification of accountability, development of digital competencies, and creation of a supportive organizational climate. Therefore, the strong effect of organizational support and training confirms that professional resistance can be reduced when accountants are actively prepared for AI-based change.

Fear of skill obsolescence was the second strongest predictor of resistance, which shows that accountants' concerns about the future value of their professional capabilities are central to their response to AI implementation. This finding is theoretically meaningful because accounting expertise has traditionally been built on mastery of standards, rules, classifications, reporting procedures, taxation, auditing principles, and professional judgment. Artificial intelligence challenges this model by performing some cognitive and analytical tasks faster and at larger scale. The result is consistent with literature suggesting that AI transforms work by changing the structure of skills required for professional survival and advancement [9, 10]. However, the finding should not be interpreted as evidence that accountants are necessarily anti-innovation. Rather, it suggests that resistance is likely to increase when professionals do not receive a convincing pathway for reskilling. Studies on digital transformation in accounting and finance have shown that the profession is moving toward data analytics, intelligent reporting, predictive modeling, and strategic decision support [4-6]. Therefore, accountants may accept AI more readily when they understand that their future role will not disappear but will shift toward interpretation, governance, advisory work, risk analysis, and validation of algorithmic outputs.

Perceived job insecurity also significantly predicted resistance to artificial intelligence. This finding indicates that accountants who believe AI may reduce employment opportunities, replace routine roles, or weaken the demand for traditional accounting labor are more likely to oppose implementation. This result is consistent with the wider literature showing that AI adoption is frequently associated with concerns about workforce displacement, role disruption, and occupational uncertainty [2, 36]. In accounting, the source of this insecurity is understandable because AI can automate repetitive tasks that once formed a substantial part of accounting work. However, previous studies also suggest that AI creates new professional opportunities when organizations redefine work around human-machine collaboration, oversight, interpretation, and strategic decision-making [25, 29]. Accordingly, the present finding suggests that job insecurity should be addressed through transparent role redesign rather than through general assurances. Accountants need to know which tasks will be automated, which responsibilities will remain human-centered, and which new skills will be rewarded. Without this clarity, resistance may function as a defensive reaction to perceived professional displacement.

The findings also showed that lack of trust in algorithmic outputs and perceived complexity of AI systems significantly increased resistance. This result is important because accounting and auditing depend on accuracy, transparency, traceability, professional skepticism, and defensible judgment. If accountants cannot understand how AI systems produce outputs, or if they doubt the reliability of algorithmic recommendations, they may be reluctant to rely on such systems in financial reporting, audit evidence evaluation, fraud detection, or risk assessment. This interpretation is consistent with research indicating that AI adoption in professional settings is strongly influenced by trust, explainability, perceived reliability, and human oversight [18-20]. In auditing, debates about AI have similarly emphasized that intelligent systems may improve audit quality through large-scale data analysis, but their usefulness depends on professional confidence in outputs, interpretability, and accountability [32]. In financial fraud detection, AI-driven approaches can improve pattern recognition and anomaly detection, yet their acceptance requires assurance that models are reliable, explainable, and aligned with financial control requirements [33]. Therefore, the significant effects of trust and complexity suggest that accountants need transparent AI tools that allow professional verification rather than opaque systems that appear to replace judgment.

Data security, ethical concerns, and professional responsibility also had a significant effect on resistance, although the effect was smaller than organizational and skill-related factors. This finding indicates that accountants are concerned about confidentiality, data governance, legal responsibility, ethical accountability, and the consequences of AI-generated financial errors. The result is consistent with studies showing that ethical and legal issues represent major barriers to AI adoption in sensitive professional domains [22-24]. Accounting data are highly sensitive, and any failure in data protection or algorithmic responsibility may create serious financial, legal, and reputational consequences. Similar concerns have been reported in healthcare, where AI implementation is shaped by privacy, accountability, patient safety, and institutional governance [12, 26]. In accounting, these concerns may be even more closely connected to professional liability because accountants and auditors must justify financial judgments to managers, regulators, shareholders, tax authorities, and external stakeholders. The finding therefore supports the view that responsible AI implementation in accounting requires clear governance rules, data protection mechanisms, audit trails, and professional accountability frameworks.

The perceived threat to professional judgment also significantly predicted resistance. Although this path had one of the smaller coefficients, it remains conceptually important because professional judgment is central to accounting and auditing. Accountants may resist AI when they believe that algorithmic systems reduce their autonomy, weaken professional skepticism, or shift decision-making authority from human experts to software. This finding aligns with discussions emphasizing that generative and intelligent technologies challenge conventional understandings of expertise, knowledge production, and professional responsibility [30]. Similar issues have been observed in libraries and information services, where AI is changing professional roles and raising questions about the relationship between human expertise and automated systems [13, 31]. In accounting, AI should therefore be framed not as a replacement for professional judgment but as a decision-support mechanism that enhances evidence collection, anomaly detection, forecasting, and analytical depth. The human-in-the-loop perspective is especially relevant here, because it emphasizes the continued need for professional oversight in AI-supported systems [25]. This interpretation suggests that resistance may decrease when accountants perceive themselves as supervisors, interpreters, and validators of AI outputs rather than passive recipients of algorithmic decisions.

The results further showed that resistance to artificial intelligence had a strong positive effect on impairment of financial digital transformation. Specifically, resistance predicted delays in adopting intelligent financial systems, reduced integration of AI into accounting and auditing processes, lower quality of data-driven financial decision-making, reduced efficiency of financial reporting, limited use of predictive financial analytics, weakness in real-time financial monitoring, and reduced organizational agility. This finding is consistent with studies showing that AI has the potential to transform financial and organizational systems by improving automation, analytics, fraud detection, decision support, and service efficiency [7, 8, 37]. However, the present study adds that these benefits may not be realized if professional users resist implementation. In this sense, resistance becomes a practical barrier to digital transformation rather than only an individual psychological response. Similar evidence from other sectors indicates that the benefits of AI are dependent on adoption conditions, stakeholder readiness, ethical governance, and responsible implementation [1, 34, 35]. Therefore, the successful digital transformation of financial functions requires simultaneous attention to technology, people, processes, and professional culture.

The mediation findings showed that resistance to AI implementation served as a central mechanism linking antecedent concerns to impairment of financial digital transformation. Insufficient organizational support and training had the strongest total effect, followed by fear of skill obsolescence, perceived job insecurity, lack of trust in algorithmic outputs, and perceived AI complexity. This means that professional and organizational concerns do not only increase resistance directly; they also indirectly weaken digital transformation by reducing accountants' willingness to engage with AI-based systems. This finding supports the broader conclusion that AI adoption is dependent on the alignment between technological innovation and human readiness [2, 3]. It also aligns with sustainable implementation perspectives, which argue that AI-supported functions require assessment of organizational capabilities, long-term value creation, operational fit, and stakeholder acceptance [28]. In accounting, the implication is clear: organizations cannot achieve financial digital transformation by purchasing AI tools alone. They must also manage professional meaning, trust, skill development, and ethical assurance. Accordingly, the final model confirms that accountants' resistance is both an outcome of perceived threats and a cause of delayed or weakened digital transformation.

This study had several limitations that should be considered when interpreting the findings. First, the study was conducted among professional accountants in Tehran, and although the sample was diverse in terms of organizational setting and professional experience, the findings may not fully represent accountants working in other provinces, smaller cities, public-sector organizations, or international financial environments. Second, the study used a cross-sectional design, which means that the relationships among variables were examined at one point in time; therefore, causal interpretations should be made with caution. Third, the data were collected through self-report questionnaires, and participants' responses may have been influenced by subjective perceptions, social desirability, or differences in their actual exposure to AI-based accounting systems. Fourth, the study examined resistance at the individual-professional level and did not directly measure organizational-level variables such as management strategy, technology budget, implementation maturity, regulatory environment, or actual AI system performance. Finally, because artificial intelligence in accounting is still developing, participants may have responded based on perceived or anticipated AI implementation rather than long-term direct experience with fully integrated AI systems.

Future studies should examine resistance to artificial intelligence among accountants in different geographical, organizational, and regulatory contexts to determine whether the pattern of findings remains stable across diverse financial environments. Longitudinal research is recommended to evaluate how accountants' resistance changes before, during, and after actual AI implementation, because professional attitudes may shift as users gain experience, receive training, and observe the real consequences of AI adoption. Future research could also compare accountants working in audit firms, corporate finance departments, banks, tax institutions, and public-sector financial units to identify sector-specific sources of resistance. In addition, qualitative studies based on interviews or focus groups could provide deeper insight into accountants' lived experiences, fears, expectations, and interpretations of AI-driven change. Future models may also include moderating variables such as digital literacy, organizational culture, leadership support, perceived usefulness, AI transparency, regulatory clarity, and prior technology adoption experience. Experimental or intervention-based studies could further examine whether targeted training, ethical assurance, participatory implementation, or human-in-the-loop system design can reduce resistance and improve readiness for financial digital transformation.

Organizations seeking to implement artificial intelligence in accounting and financial processes should treat resistance as a strategic implementation issue rather than as a personal weakness among accountants. Before introducing AI-based systems, managers should communicate clearly about the purpose of implementation, expected changes in work roles, limits of automation, and the continuing importance of professional judgment. Training programs should be practical, continuous, and role-specific, helping accountants understand how AI tools operate, how outputs can be interpreted, and how professional responsibility will be maintained. Organizations should also involve accountants in system selection, testing, evaluation, and redesign so that implementation becomes participatory rather than imposed. Clear policies are needed for data protection, algorithmic accountability, audit trails, ethical use, and responsibility for AI-supported decisions. Professional bodies and accounting educators should update curricula and continuing education programs to include AI literacy, data analytics, digital auditing, cybersecurity awareness, and responsible technology use. Most importantly, AI should be presented as a tool that strengthens accountants' analytical and advisory roles, not as a replacement for professional expertise.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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