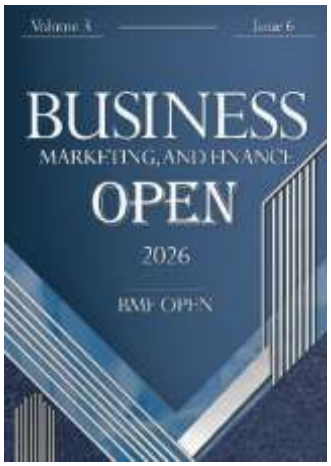
Examining the Factors Influencing the Adoption of Artificial Intelligence in the Accounting Profession

Vahid Sheykholmolouki[1], Javad Ramezani[2,*], Yousef Taghipourian[3] and Mehdi Khalilpour[4]



[1] Department of Accounting, No.C., Islamic Azad University, Noor, Iran;
[2] Associate Professor, Department of Accounting, No.C., Islamic Azad University, Noor, Iran;
[3] Assistant professor, Department of Accounting, Cha.C., Islamic Azad University, Chalus, Iran;
[4] Assistant Professor, Department of Accounting, No.C., Islamic Azad University, Noor, Iran;

* Correspondence: javad.ramezani58@iau.ac.ir

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Abstract: Accounting and auditing firms are undergoing a paradigm shift due to the integration of artificial intelligence (AI), which has the potential to bring about fundamental transformations in critical areas such as improving the accuracy of financial reporting, enhancing audit efficiency, and reducing information asymmetry. However, the effectiveness of AI adoption in achieving these objectives is not guaranteed. Accordingly, this study seeks to empirically examine the factors that influence the adoption of AI among accounting and auditing firms. Initially, a set of models and factors affecting the adoption of AI was extracted from the literature and expert opinions and classified into three categories: technological, organizational, and environmental factors. Subsequently, the most important factors within each category were collected through a questionnaire, and the Friedman ranking test was used to identify the most and least significant criteria within each category. In order to weight and prioritize the factors, a quantitative approach employing the Best–Worst Method (BWM) was applied. The statistical population consisted of 30 experts actively involved in AI within accounting firms and auditing institutions. Based on the results obtained, organizational factors were identified as the most influential, followed by technological factors in second place and environmental factors in third place in terms of AI adoption. Moreover, top management support within the organizational dimension, ease of use and learning within the technological dimension, and required standards for development within the environmental dimension were identified as the most important sub-factors. These findings not only contribute to the advancement of scholarly discussions on AI adoption in the financial and accounting domain but also provide practical strategies for stakeholders to maximize the benefits of this transformative technology.

Keywords: Artificial Intelligence; Accounting and Auditing Firms; Technology Adoption; Best–Worst Method

1. Introduction

The rapid advancement of artificial intelligence (AI) has profoundly reshaped organizational processes, decision-making structures, and value creation mechanisms across industries, with the accounting and auditing profession being no exception. Accounting has traditionally been regarded as a rule-based, standardized, and compliance-oriented profession; however, the integration of AI-driven technologies such as machine learning, robotic process automation, big data analytics, and blockchain-enabled systems has fundamentally altered how accounting information is generated, processed, and interpreted [1, 2]. These technological shifts have accelerated the

automation of routine accounting tasks, enhanced real-time reporting capabilities, and enabled more sophisticated analytical and predictive functions, thereby redefining the strategic role of accountants and auditors within organizations [3, 4]. As a result, AI is no longer perceived merely as a supporting tool but as a transformative force capable of reshaping the entire accounting ecosystem.

One of the most prominent promises of AI adoption in accounting lies in its potential to improve financial reporting accuracy, enhance audit efficiency, and reduce information asymmetry between firms and stakeholders. Advanced AI algorithms can process vast volumes of structured and unstructured data with greater speed and precision than traditional systems, thereby minimizing human error and judgment bias in financial reporting [5]. Similarly, AI-enabled audit tools facilitate continuous auditing, anomaly detection, and risk assessment, allowing auditors to focus on higher-level professional judgment rather than manual verification tasks [6]. By improving transparency and timeliness of information, AI also contributes to mitigating information asymmetry, which has long been recognized as a critical challenge in financial markets and corporate governance [7, 8]. Despite these potential benefits, empirical evidence suggests that the actual adoption and effective utilization of AI within accounting firms remain uneven and context-dependent.

The gap between the theoretical benefits of AI and its practical implementation highlights the importance of understanding the determinants of AI adoption in the accounting profession. Adoption of complex technologies is not solely a technical decision; rather, it is a multifaceted organizational process influenced by technological readiness, organizational capabilities, environmental pressures, and institutional frameworks [9]. Prior research on technology adoption emphasizes that even highly beneficial innovations may fail to diffuse if organizations lack the necessary infrastructure, managerial support, or regulatory clarity [10, 11]. In the accounting context, resistance to change, concerns about data security, ethical implications, professional judgment displacement, and skills mismatch have been frequently cited as barriers to AI adoption [6, 12]. Therefore, a systematic investigation of adoption factors is essential for translating AI's technical potential into sustainable professional practice.

The Technology Acceptance Model (TAM) has been widely used to explain individual-level acceptance of information systems, emphasizing perceived usefulness and perceived ease of use as key predictors of adoption [13]. While TAM provides valuable insights into user perceptions, it has been criticized for its limited ability to capture organizational and environmental influences that are particularly relevant for complex technologies such as AI. To address this limitation, scholars have increasingly adopted the Technology–Organization–Environment (TOE) framework, which conceptualizes adoption as the outcome of interactions between technological characteristics, organizational conditions, and environmental context [11, 14]. In the accounting and auditing domain, the TOE framework has proven effective in explaining variations in AI adoption across sectors, firm sizes, and institutional settings [15, 16].

Within the technological dimension, factors such as system compatibility, data quality, cybersecurity, perceived reliability, and ease of use play a decisive role in shaping adoption decisions. Accounting firms operate in highly regulated environments where data integrity and confidentiality are paramount; thus, any perceived technical vulnerability can significantly hinder AI implementation [12]. Moreover, the integration of AI with existing accounting information systems and enterprise resource planning platforms remains a critical challenge, particularly for small and medium-sized firms with limited IT capabilities [10]. Empirical studies indicate that when AI systems are perceived as user-friendly and compatible with existing workflows, resistance among accounting professionals is substantially reduced [16, 17].

Organizational factors are equally influential in determining AI adoption outcomes. Top management support, availability of financial resources, employee competencies, organizational culture, and strategic alignment have been repeatedly identified as central drivers of successful digital transformation [11, 14]. In accounting firms, leadership commitment is particularly critical, as AI adoption often requires redefining roles, redesigning processes, and investing in continuous professional training [6]. Without explicit managerial endorsement and resource allocation, AI initiatives are likely to remain pilot projects rather than becoming embedded in routine professional practice [15]. Furthermore, the shortage of AI-related skills among accounting professionals underscores the importance of organizational learning and capacity-building mechanisms [17].

Beyond internal organizational conditions, environmental factors exert substantial influence on AI adoption in the accounting profession. Competitive pressure, regulatory frameworks, professional standards, and governmental support shape the external context in which accounting firms operate. In highly competitive markets, firms may adopt AI as a strategic response to maintain efficiency, enhance service quality, and differentiate themselves from competitors [16]. Conversely, regulatory ambiguity and the absence of clear professional standards for AI-based accounting practices can create uncertainty and inhibit adoption [12]. Studies conducted in public sector and emerging economy contexts further demonstrate that government policies, digital infrastructure, and institutional trust play a pivotal role in accelerating or constraining AI diffusion [15, 18].

Recent research has also highlighted the interdependence between AI adoption and broader digital ecosystems, including big data governance, blockchain technologies, and social media-driven information flows. Effective AI implementation in accounting increasingly depends on the organization's ability to manage data strategically and align AI initiatives with dynamic capabilities [19]. At the same time, emerging technologies such as blockchain are reshaping assurance and audit processes, creating new complementarities and challenges for AI-based systems [2, 4]. These developments suggest that AI adoption should be examined not in isolation, but as part of a broader technological and institutional transformation within the accounting profession.

Despite the growing body of literature on AI and digital transformation, empirical studies focusing specifically on the determinants of AI adoption in accounting and auditing remain relatively limited and fragmented. Existing research often concentrates on single-country contexts, specific sectors, or individual technologies, thereby constraining the generalizability of findings [6, 15]. Moreover, many studies rely on single theoretical lenses, overlooking the complex interactions between technological, organizational, and environmental factors. Recent integrative models that combine TOE with TAM, diffusion theory, and resource dependence perspectives have called for more comprehensive empirical investigations [5, 14]. Addressing this gap is particularly important in light of the accelerating pace of AI innovation and the increasing strategic importance of accounting information in organizational decision-making.

Furthermore, ethical considerations, professional integrity, and trust have emerged as critical yet underexplored dimensions of AI adoption in accounting. Concerns related to algorithmic transparency, accountability, and potential erosion of professional judgment continue to influence practitioners' attitudes toward AI [12]. Research in adjacent domains, such as higher education and enterprise innovation, suggests that individual values, integrity perceptions, and governance mechanisms significantly shape technology diffusion outcomes [20, 21]. Translating these insights into the accounting context requires systematic empirical analysis grounded in established adoption frameworks.

In summary, while AI holds transformative potential for the accounting and auditing profession, its successful adoption depends on a complex constellation of technological, organizational, and environmental factors. A

nuanced understanding of these factors is essential for scholars seeking to advance theory and for practitioners and policymakers aiming to design effective adoption strategies. Drawing on the Technology–Organization–Environment framework, diffusion of innovations theory, and recent empirical evidence, this study seeks to provide a comprehensive analysis of the key factors influencing AI adoption in the accounting and auditing profession, with the aim of informing both academic discourse and practical decision-making.

Accordingly, the aim of this study is to empirically identify and prioritize the technological, organizational, and environmental factors influencing the adoption of artificial intelligence in the accounting and auditing profession.

2. Methodology

The present study is applied in nature, and its objective is to analyze the factors influencing the adoption of artificial intelligence in the accounting and auditing profession. A mixed-methods research design was employed to identify adoption factors and to evaluate the importance of the factors affecting AI adoption. In the first stage, adoption factors used in the field of artificial intelligence were identified through a systematic literature review and were then presented to 13 experts in the accounting profession. These experts made the necessary revisions and finalized the set of factors by adding certain overlooked yet important factors. The criteria for expert selection included having at least 10 years of professional experience, participation in at least three artificial intelligence projects, and educational background related to artificial intelligence. Experts were selected using the snowball sampling method. The stopping criterion for expert selection was reached when it was observed that, after the 11th expert, the inclusion of additional experts no longer affected the identified adoption factors. Given the large number of factors, an effort was made to reduce the number of factors using the Friedman test. The research questionnaire employed a five-point Likert scale, in which respondents were asked to indicate the extent to which each factor influences the adoption of artificial intelligence. The content validity of the questionnaire was confirmed by five experts who were randomly selected. The reliability of the study was assessed using Cronbach's alpha. In the second stage of the research, the Best–Worst Method was used to determine the relative importance of the indicators identified in the first stage. For this purpose, a questionnaire was designed in accordance with the Best–Worst Method and was then distributed to 30 experts using a network-based approach. The experts included individuals who were familiar with artificial intelligence, had academic backgrounds related to artificial intelligence, possessed at least 10 years of work experience in the relevant sectors, and had participated in at least two artificial intelligence–related projects.

Decision-making is one of the most influential aspects of human life and is generally defined as the selection of one option from among the best available alternatives. When a decision-making problem involves more than one criterion, it is referred to as multi-criteria decision-making. Multi-criteria decision-making is typically conducted in two stages: determining the weights of the criteria and selecting or ranking alternatives based on those criteria. For determining criteria weights, two categories of methods exist: objective and subjective methods. Subjective methods depend on the preferences of decision-makers, whereas objective methods determine criteria weights based on the information contained in the decision matrix. Since decision matrix information is often not readily available, subjective methods are more widely used. One of the most important subjective weighting methods is the Analytic Hierarchy Process (AHP), in which final weights are determined based on information obtained from pairwise comparisons of criteria conducted by experts. A major limitation of the Analytic Hierarchy Process is that, as the number of criteria and experts increases, the number of pairwise comparisons also increases, leading to a higher likelihood of inconsistency in judgments. To address this limitation, the Best–Worst Method was first introduced

by Rezaei (2015) for weighting and ranking criteria in multi-criteria decision-making problems. The main advantage of this method compared with other weighting techniques is that, instead of conducting pairwise comparisons among all criteria, it only requires pairwise comparisons between the best criterion and the other criteria, as well as between the other criteria and the worst criterion. Moreover, compared with the Analytic Hierarchy Process, this method has two major advantages: first, it requires significantly fewer pairwise comparisons, and second, the results exhibit a higher level of consistency.

3. Findings and Results

To analyze the factors influencing the adoption of artificial intelligence in the accounting and auditing profession, international articles indexed in the Scopus database and domestic articles indexed in the Scientific Information Database (SID) and the Iranian Research Institute for Information Science and Technology (IRANDOC) were first reviewed. The final search keywords included "artificial intelligence," "machine learning," and "technology adoption," which ultimately led to the selection of 12 international articles and 9 domestic articles relevant to the topic. After a thorough review of adoption factors identified in previous studies, the factors were classified into three dimensions—technological, organizational, and environmental—and a total of 16 factors (6 technological, 6 organizational, and 4 environmental) were initially identified. Finally, based on expert panel sessions, the identified factors were categorized into the three dimensions of technology, organization, and environment, as presented in Table 1. It should be noted that, according to expert opinions, three additional criteria were added, resulting in a final set of 19 criteria (6 technological, 6 organizational, and 7 environmental) considered as factors influencing the adoption of artificial intelligence.

Table 1. Summary of Factors Related to the Adoption and Implementation of Artificial Intelligence Technology

Code	Dimension	Influential Factors	Source
C1	Technological	Adequate support from service providers	Abdolvand & Tarani (2014); Gummadidala et al. (2020)
C2		Acceptable technical safety and security	Abdolvand & Tarani (2014); Yaghoubi et al. (2014); Noordt & Misuraca (2020); Alsheibani et al. (2019)
C3		Increased efficiency and productivity	Abdolvand & Tarani (2014); Ghorbani-Zadeh et al. (2013); Dasgupta & Wendler (2019)
C4		Time and cost savings	Abdolvand & Tarani (2014); Taherkhani (2014); Noordt & Misuraca (2020)
C5		Ease of use and ease of learning	Heydariyeh et al. (2013); Yaghoubi et al. (2014); Hosseini et al. (2017); Ghorbani-Zadeh et al. (2013); Noordt & Misuraca (2020)
C6		Compatibility with existing infrastructures	Taherkhani (2020); Hosseini et al. (2017); Haghighi-Nasab & Taghavi (2020); Ghorbani-Zadeh et al. (2013)
C7	Organizational	Top management support	Hosseini & Forouzanfar (2018); Yaghoubi et al. (2014); Taherkhani (2020); Haghighi-Nasab & Taghavi (2020); Radhakrishnan et al. (2020); Gummadidala et al. (2020); Alsheibani et al. (2019)
C8		Skilled and competent human resources	Hosseini & Forouzanfar (2018); Abdolvand & Tarani (2014); Heydariyeh et al. (2013); Haghighi-Nasab & Taherkhani (2020); Taghavi (2020); Hosseini et al. (2017); Radhakrishnan et al. (2020); Alsheibani et al. (2019); Concepcion et al. (2019)
C9		Financial resources	Abdolvand & Tarani (2014); Alsheibani (2018); Concepcion et al. (2019)
C10		Required infrastructures	Hosseini & Forouzanfar (2018); Abdolvand & Tarani (2014); Hosseini et al. (2017); Radhakrishnan et al. (2020); Concepcion et al. (2019); Alsheibani et al. (2018)
C11		Relevant training programs	Heydariyeh et al. (2013); Hosseini et al. (2017)
C12		Strategic programs for development and implementation	Mutawa & Rashid (2020); Radhakrishnan et al. (2020); Concepcion et al. (2019)

C13	Environmental	Required standards for development	Hosseini et al. (2017)
C14		Competitive pressure	Taherkhani (2020); Ghorbani-Zadeh (2013); Radhakrishnan et al. (2020); Alsheibani et al. (2018); Dasgupta & Wendler (2019)
C15		Legal gaps	Mutawa & Rashid (2020); Taherkhani (2020); Noordt & Misuraca (2020); Alsheibani et al. (2018); Dasgupta & Wendler (2019); Gummadidala et al. (2020); Concepcion et al. (2019)
C16		Government support	Rao & Verweij (2017); Dasgupta & Wendler (2019)
C17		Pressure from customers and users	Experts
C18		Business development incubators	Experts
C19		Coordination among relevant institutions	Experts

To determine the importance of the factors, expert opinions were first collected using a questionnaire. Subsequently, in order to analyze the data, the Kolmogorov–Smirnov test was employed to determine and assess the distribution type of the data obtained from the questionnaire. The test results indicated that the questionnaire data did not follow a normal statistical distribution; therefore, the data were treated as distribution-free, and nonparametric (distribution-free) tests were used for analysis. Accordingly, the Friedman ranking test was applied to rank the identified factors. To assess the degree of importance of the factors, a questionnaire based on a five-point Likert scale was designed, in which experts were asked to indicate their level of agreement regarding the importance of each factor. Based on the Friedman test results, the most important main factor was "technology," while the least important main factor was "environmental." For each main factor, the most important and least important sub-factors are presented in the table below.

Table 2. Most Important and Least Important Factors for Adoption Dimensions

Main Factor	Most Important Sub-Factor	Least Important Sub-Factor
Organizational	Top management support	Strategic programs for development and implementation
Technological	Ease of use and ease of learning	Compatibility with existing infrastructures
Environmental	Required standards for development	Legal gaps

To determine the weights of the main factors, the pairwise comparison vector of the best factor relative to the other criteria and the pairwise comparison vector of the other criteria relative to the worst criterion were specified. Finally, using the model, the weights of the main factors and sub-factors were calculated. The following tables present the pairwise comparison vectors for the main factors and sub-factors.

Table 3. Pairwise Comparison Vector of the Best Main Factor Relative to Other Factors

Main Factors	Organizational	Environmental
Technological	3.0	2.0

Table 4. Pairwise Comparison Vector of Main Factors Relative to the Worst Adoption Factor

Main Factors	Value
Technological	5.3
Environmental	2.0

Table 5. Pairwise Comparison Vector of the Best Technological Sub-Factor Relative to Other Sub-Factors

Technological Sub-Factors	C1	C2	C3	C4	C5	C6
Ease of use and ease of learning	1.0	1.2	1.7	3.7	1.6	2.0

Table 6. Pairwise Comparison Vector of Technological Sub-Factors Relative to the Least Important Sub-Factor

Technological Sub-Factors	C1	C2	C3	C4	C5	C6
C6	2.5	2.0	2.0	2.0	3.5	1.0

Table 7. Pairwise Comparison Vector of the Best Organizational Sub-Factor Relative to Other Sub-Factors

Organizational Sub-Factors	C7	C8	C9	C10	C11	C12
Top management support	1.0	1.2	1.2	1.3	1.7	1.2

Table 8. Pairwise Comparison Vector of Organizational Sub-Factors Relative to the Least Important Sub-Factor

Organizational Sub-Factors	C7	C8	C9	C10	C11	C12
C12	3.0	3.0	3.1	2.8	1.0	1.2

Table 9. Pairwise Comparison Vector of the Best Environmental Sub-Factor Relative to Other Sub-Factors

Environmental Sub-Factors	C13	C14	C15	C16	C17	C18	C19
Required standards for development	1.5	1.3	1.5	1.5	—	—	—

Table 10. Pairwise Comparison Vector of Environmental Sub-Factors Relative to the Least Important Sub-Factor

Environmental Sub-Factors	C13	C14	C15	C16	C17	C18	C19
C15	2.2	1.5	1.6	1.3	—	—	—

Table 11. Final Definitive Weights of Main Factors and Adoption Sub-Factors Based on the Best–Worst Method

Code	Dimension	Influential Factors	Final Sub-Factor Weight	Final Factor Weight
C1	Technological	Adequate support from service providers	0.055	0.481
C2		Acceptable technical safety and security	0.059	
C3		Increased efficiency and productivity	0.092	
C4		Time and cost savings	0.080	
C5		Ease of use and ease of learning	0.149	
C6		Compatibility with existing infrastructures	0.098	
C7	Organizational	Top management support	0.144	0.321
C8		Skilled and competent human resources	0.122	
C9		Financial resources	0.115	
C10		Required infrastructures	0.124	
C11		Relevant training programs	0.068	
C12		Strategic programs for development and implementation	0.068	
C13	Environmental	Required standards for development	0.102	0.290
C14		Competitive pressure	0.062	
C15		Legal gaps	0.077	
C16		Government support	0.102	
C17		Pressure from customers and users	0.055	
C18		Business development incubators	0.128	
C19		Coordination among relevant institutions	0.082	

Tables 3 to 11 report the results of the Best–Worst Method (BWM) used to prioritize the main dimensions and sub-factors influencing artificial intelligence adoption in the accounting and auditing profession. As shown in Tables 3 and 4, the pairwise comparison vectors indicate that the technological dimension was identified as the best (most important) main factor, while the environmental dimension was considered the worst (least important), resulting in the highest final weight for technology (0.481), followed by organizational factors (0.321) and environmental factors (0.290). Tables 5 and 6 present the pairwise comparison vectors for technological sub-factors, demonstrating that "ease of use and ease of learning" (C5) was selected as the best technological sub-factor, whereas "compatibility with existing infrastructures" (C6) was identified as the least important benchmark, leading to C5 receiving the highest technological sub-factor weight (0.149). Tables 7 and 8 report the organizational sub-factor comparisons, where "top management support" (C7) emerged as the best organizational sub-factor and "strategic programs for development and implementation" (C12) as the least important, with C7 obtaining the highest organizational sub-factor weight (0.144). Tables 9 and 10 show the environmental sub-factor comparisons, indicating that "required standards for development" (C13) was the best environmental sub-factor and "legal gaps" (C15) the least important reference, resulting in relatively higher weights for C13 (0.102) and other environment-related factors such as government support (C16 = 0.102) and business development incubators (C18 = 0.128). Finally, Table 11 summarizes the final definitive weights of all main factors and sub-factors, confirming that technological usability and performance-related factors dominate AI adoption decisions, organizational leadership and resource-related factors play a strong enabling role, and environmental factors, while comparatively less influential, still contribute meaningfully to shaping the overall adoption framework.

4. Discussion and Conclusion

The findings of the present study provide a nuanced understanding of the relative importance of technological, organizational, and environmental factors in shaping the adoption of artificial intelligence in the accounting and auditing profession. Overall, the results indicate that technological factors constitute the most influential dimension, followed by organizational factors, while environmental factors play a comparatively less decisive—yet still meaningful—role in AI adoption. This hierarchy of factors underscores the centrality of system-related characteristics and user interaction issues in determining whether AI solutions are embraced by accounting professionals, which is broadly consistent with established technology adoption theories and prior empirical evidence [9, 14].

At the technological level, the prominence of "ease of use and ease of learning" as the most important sub-factor highlights the critical role of perceived usability in fostering acceptance of AI systems among accountants and auditors. This result aligns closely with the core assumptions of the Technology Acceptance Model, which posits that perceived ease of use significantly influences attitudes toward new technologies and subsequent adoption behavior [13]. In the accounting context, where professionals often operate under time pressure and strict compliance requirements, technologies that are complex or require extensive retraining are likely to face resistance. Similar findings have been reported in studies examining AI and advanced analytics adoption, which emphasize that intuitive interfaces and user-friendly system design substantially lower psychological and operational barriers to adoption [16, 17]. The present results therefore reinforce the argument that AI developers and vendors targeting the accounting profession must prioritize usability and learning efficiency alongside technical sophistication.

Closely related to ease of use, the relatively high weights assigned to "increased efficiency and productivity" and "compatibility with existing infrastructures" further emphasize that accounting firms adopt AI primarily when

it demonstrably enhances performance and integrates smoothly with established information systems. These findings resonate with prior research showing that productivity gains and workflow compatibility are decisive technological drivers of digital transformation in accounting and auditing [1, 2]. In particular, compatibility reduces the need for costly system overhauls and mitigates operational disruption, which is especially important for small and medium-sized accounting firms with limited IT resources [10]. This supports earlier evidence that perceived technological fit plays a more critical role than novelty or innovation appeal in professional service contexts [11].

Interestingly, while issues related to technical safety and security were found to be important, they did not emerge as the most critical technological determinant. This suggests that, although data security and system reliability remain fundamental prerequisites, accounting professionals may increasingly view them as baseline expectations rather than differentiating factors. Similar interpretations have been offered in studies on AI and big data adoption, which argue that as cybersecurity standards mature, users shift their focus toward value-adding functionalities rather than mere risk avoidance [12, 19]. Nonetheless, the continued relevance of security concerns in the findings indicates that neglecting this aspect could still undermine trust and adoption, particularly in highly regulated accounting and auditing environments.

With respect to organizational factors, "top management support" emerged as the most influential sub-factor, underscoring the pivotal role of leadership commitment in driving AI adoption. This result is strongly aligned with the Technology–Organization–Environment framework, which emphasizes managerial support as a key organizational enabler of technological innovation [14]. In accounting firms, top management not only allocates financial and human resources but also shapes organizational culture and attitudes toward technological change. Prior empirical studies in both private and public sector accounting contexts similarly report that visible endorsement by senior leadership significantly increases the likelihood of successful AI implementation [15, 16]. The present findings thus reaffirm that AI adoption is not merely a technical initiative but a strategic organizational decision requiring sustained managerial engagement.

Other organizational sub-factors, such as the availability of skilled and competent human resources and adequate financial resources, also received substantial weights, highlighting the importance of internal capabilities in supporting AI-driven transformation. Accounting and auditing professionals require new competencies, including data analytics literacy and an understanding of AI-driven decision tools, to effectively interact with intelligent systems. This finding is consistent with prior research emphasizing that skill gaps and insufficient training remain major obstacles to AI adoption in professional service firms [6, 17]. Furthermore, the significant weight attributed to required infrastructures suggests that AI adoption depends on a broader organizational readiness that encompasses hardware, software, and data management capabilities, echoing earlier work on enterprise system adoption [10, 11].

In contrast, strategic programs for AI development and implementation were identified as the least important organizational sub-factor. This may indicate that, in the early or intermediate stages of AI diffusion within accounting firms, practical leadership support and operational readiness outweigh formalized strategic planning. Similar patterns have been observed in emerging technology adoption, where informal experimentation and managerial championing often precede the formulation of comprehensive digital strategies [18]. However, as AI adoption matures, the relative importance of formal strategies may increase, suggesting a dynamic relationship between organizational factors and adoption stages.

Environmental factors, although ranked as the least influential main dimension, nonetheless play a meaningful role in shaping AI adoption decisions. Among environmental sub-factors, "required standards for development"

emerged as the most important, highlighting the significance of regulatory clarity and professional guidelines in legitimizing AI use in accounting and auditing. This finding is consistent with prior studies emphasizing that ambiguity in standards and regulations can deter firms from adopting advanced technologies due to compliance risks and legal uncertainty [12, 15]. Clear standards provide a framework for acceptable AI practices, thereby reducing perceived risk and facilitating broader diffusion.

Conversely, "legal gaps" were identified as the least important environmental sub-factor, which may initially appear counterintuitive. One possible interpretation is that accounting firms have learned to operate within imperfect regulatory environments and may prioritize immediate operational benefits over unresolved legal concerns, particularly when competitive pressures are strong. Similar observations have been reported in studies on blockchain and AI adoption, where firms proceed with implementation despite regulatory ambiguity, relying on professional judgment and incremental compliance adjustments [2, 4]. Nevertheless, this does not imply that legal considerations are irrelevant; rather, their influence may be indirect or moderated by organizational risk tolerance and market dynamics.

The moderate importance assigned to factors such as competitive pressure and government support further suggests that external forces can act as catalysts rather than primary drivers of AI adoption. Competitive environments may encourage firms to explore AI to enhance efficiency and service quality, while supportive government policies and digital infrastructure can accelerate diffusion, particularly in public sector or emerging economy contexts [15, 16]. These findings align with diffusion of innovations theory, which posits that environmental context influences the rate and pattern of adoption rather than determining adoption outright [9].

Taken together, the results of this study support an integrated perspective on AI adoption in accounting, in which technological usability and performance benefits form the core drivers, organizational leadership and capabilities act as critical enablers, and environmental conditions provide contextual support or constraints. This pattern is consistent with recent integrative models combining TOE, TAM, and resource-based perspectives, which emphasize the interplay between internal and external factors in shaping technology adoption outcomes [5, 14]. By empirically prioritizing these factors, the present study extends the existing literature and offers a more granular understanding of how AI adoption unfolds in the accounting and auditing profession.

Despite its contributions, this study has several limitations that should be acknowledged. First, the reliance on expert judgments and survey-based data may introduce subjectivity and potential response bias, as perceptions of importance can vary based on individual experience and organizational context. Second, the study focuses on a specific professional and institutional setting, which may limit the generalizability of the findings to other countries or sectors with different regulatory and technological environments. Third, the cross-sectional design captures adoption factors at a single point in time and does not account for the dynamic evolution of AI adoption as technologies and organizational capabilities mature.

Future research could build on the present study by employing longitudinal designs to examine how the importance of adoption factors changes over time as AI technologies become more embedded in accounting practice. Comparative studies across countries, sectors, or firm sizes would also enhance understanding of contextual variations in AI adoption. Additionally, future studies could integrate qualitative approaches, such as in-depth interviews or case studies, to explore the underlying mechanisms through which organizational culture, professional identity, and ethical considerations influence AI adoption in accounting and auditing.

From a practical perspective, accounting and auditing firms should prioritize investments in user-friendly AI systems that integrate seamlessly with existing workflows and demonstrably enhance efficiency. Senior managers

are encouraged to play an active leadership role by endorsing AI initiatives, allocating sufficient resources, and fostering a learning-oriented culture that supports skill development. Policymakers and professional bodies can further facilitate AI adoption by developing clear standards and guidelines that reduce uncertainty and build trust in AI-based accounting practices.

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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