Assessing the Adoption of Artificial Intelligence Technology in Management Accounting Sustainability Reporting

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ABSTRACT

Objective: This study aims to assess the acceptance of artificial intelligence technology in the field of management accounting modernization and digitalization, especially in the field of sustainability reporting.
Method: The present study is descriptive-survey and was conducted using a questionnaire. The sample size of 120 people was determined based on the Cochran formula. Data analysis was performed using structural equation modeling with the partial least squares (PLS) approach and Smart PLS software.
Findings: The results showed that the average of perceived usefulness (4.005), perceived ease of use (3.848) and behavioral intention (3.687) are at a high level. Confirmatory factor analysis indicates strong measurement validity with factor loadings above 0.5 and reliability indices (Cronbach's alpha and CR) above 0.7. The coefficients of determination of the dependent variables above 0.67 and the goodness of fit index (GOF) equal to 0.811 indicate a strong explanatory power of the model.
Results: Hypothesis testing showed that perceived usefulness (path coefficient = 0.345) and perceived ease of use (path coefficient = 0.886) have a significant effect on behavioral intention, with the difference that the effect of perceived ease of use is stronger. Also, behavioral intention has a strong and significant effect (path coefficient = 0.857) on the actual use of AI solutions. These findings indicate a generally positive attitude towards the adoption of AI in management accounting, but indicate that in the Iranian business context, the ease of implementing AI technologies is a more important factor in creating adoption intention.

Keywords: Artificial Intelligence, Management Accounting, Sustainability Reporting, Technology Acceptance Model, Structural Equation Model

1. Introduction

Artificial intelligence (AI), as one of the most significant emerging technologies of the 21st century, is fundamentally transforming various industries, including accounting. With its advanced capabilities in data processing, pattern recognition, and autonomous decision-making, this technology is undergoing rapid and continuous changes that facilitate its application across diverse business sectors (Brynjolfsson & McAfee, 2017). Recent advancements in machine learning, natural language processing, and big data analytics have paved the way for widespread AI applications in commercial domains (McAfee & Brynjolfsson, 2017).

In the field of accounting, artificial intelligence has played a significant role in transforming traditional processes. By enabling the automation of complex accounting procedures, from data collection and classification to advanced financial information analysis, this technology has improved the quality and speed of accounting service delivery (Kokina & Davenport, 2017; Sutton et al., 2016). The use of AI in accounting has not only enhanced computational accuracy but also enabled the analysis of complex financial patterns and the provision of better strategic insights (Frey & Osborne, 2017).

Amidst the growing concept of sustainability and corporate social responsibility, sustainability reporting has emerged as a vital tool for organizational transparency and accountability. Management accounting, with its focus on providing internal information for managerial decision-making, plays a key role in preparing and presenting sustainability reports (Kolk, 2003). The integration of AI into management accounting's sustainability reporting processes facilitates the processing of vast volumes of non-financial data, the analysis of complex sustainability indicators, and the provision of more comprehensive reports (Gray et al., 2016; Bebbington & Unerman, 2018).

Despite the clear advantages of artificial intelligence, the adoption of this technology in organizations faces significant challenges. Employee resistance to change, concerns about job security, a lack of necessary technical skills, and the fear of human labor replacement by machines are among the main obstacles to AI adoption in workplaces (Venkatesh et al., 2003). Furthermore, the scarcity of specialized and skilled personnel in new technologies has been identified as one of the greatest challenges facing organizations in leveraging AI (Rogers, 2003; Davis, 1989).

In the Iranian context, domestic companies are also facing the necessity of digitalizing and modernizing their accounting processes. Given the increasing importance of sustainability reporting in the international arena and competitive pressures for greater transparency, Iranian companies have an urgent need to utilize advanced technologies in management accounting (Schaltegger & Burritt, 2017). Investigating the adoption of AI technology in management accounting's sustainability reporting within Iranian companies can provide valuable insights into the factors influencing this adoption and offer practical solutions for improving implementation processes.

The present study aims to fill the existing gap in the research literature concerning the adoption of AI technology in management accounting, with a specific focus on its application in sustainability reporting. By examining the factors influencing AI adoption in Iranian companies, this research offers a deeper understanding of the challenges and opportunities in this field and can pave the way for developing effective strategies for successful implementation of this technology within the Iranian context (Ajzen, 1991; Fishbein & Ajzen, 1975).

The future structure of the research is as follows: First, the theoretical foundations and research background, along with related concepts and previous studies in this field, will be reviewed. Subsequently, the research methodology, including the research approach, target population, research variables, and machine learning models used, will be explained. Next, the findings from the implementation of the models and a comparison of the performance of different methods in the studied markets will be presented. Finally, the conclusion and practical applications of the research will be provided.

Research background

Artificial intelligence (AI), as a technology capable of simulating human intelligence, has brought profound transformations to the field of accounting in recent decades. According to Russell and Norvig (2020), AI encompasses systems capable of logical thinking, learning, and performing human-like actions. In accounting, this technology has found specific applications in areas such as automated document processing, fraud detection, predictive analytics, and intelligent reporting (Kokina & Davenport, 2017). Studies indicate that using machine learning algorithms in accounting can increase data processing accuracy by up to 95% and significantly reduce the time required for accounting processes (Sutton et al., 2016). Furthermore, AI has enabled the analysis of vast amounts of financial and non-financial data, allowing accountants to focus on strategic and advisory analyses (Zhang et al., 2018).

Sustainability reporting has evolved from an optional approach to a strategic necessity over the past two decades. The European Commission defines sustainability reporting as "the disclosure of information relating to a company's environmental, social, and governance impacts" (European Commission, 2014). Management accounting plays a pivotal role in this process by providing the necessary information systems and analytical tools for collecting, processing, and reporting sustainability data (Schaltegger & Burritt, 2017). A study by Adams and Frost (2008) indicates that companies with stronger management accounting systems for sustainability reporting demonstrate better performance on ESG (Environmental, Social, and Governance) indicators. Moreover, Bebbington and Unerman (2018) emphasize that management accounting should extend beyond traditional financial metrics to encompass multidimensional sustainability indicators.

The integration of novel technologies into sustainability reporting has led to fundamental changes in this field. Technologies such as blockchain, the Internet of Things (IoT), and artificial intelligence have enabled real-time data collection, verification of information transparency, and advanced analytics (Seele, 2017). A study by Geissdoerfer et al. (2018) shows that using digital technologies in sustainability reporting can improve information quality by up to 40% and reduce data collection costs by up to 60%. Additionally, Jones and Slack (2019) note in their study that AI has the ability to detect hidden patterns in sustainability data that are not discernible to humans, leading to the discovery of new insights and improved sustainability strategies.

Understanding the factors influencing technology adoption requires leveraging robust behavioral theories. However, existing theoretical frameworks demonstrate significant limitations when applied to specialized contexts such as AI adoption in sustainability reporting. A critical examination of the dominant models reveals three fundamental theoretical gaps that necessitate a novel integrated approach. The Technology Acceptance Model (TAM), introduced by Davis (1989), posits perceived usefulness and perceived ease of use as primary predictors of behavioral intention technology. While TAM has shown consistent predictive validity across general technology contexts ($R^2 = 0.40\text{-}0.60$), its explanatory power diminishes significantly in professional accounting environments ($R^2 = 0.25\text{-}0.35$) (Gefen & Straub, 2000), suggesting that domain-specific factors are inadequately captured by the original model. The Theory of Planned Behavior (TPB), developed by Ajzen (1991), identifies attitude, subjective norms, and perceived behavioral control as determinants of behavioral intention. However, TPB's focus on individual-level factors fails to account for organizational and environmental pressures that are particularly influential in professional technology adoption contexts (Venkatesh et al., 2003). Recent studies indicate that the UTAUT2 model (Unified Theory of Acceptance and Use of Technology), developed by Venkatesh et al. (2012), has higher accuracy in predicting the adoption of advanced technologies. This model considers factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value. Despite UTAUT2's comprehensive approach, its application in sustainability reporting contexts reveals a critical limitation: the model's generic performance expectancy construct fails to capture the unique stakeholder accountability and legitimacy concerns that drive sustainability technology adoption (Lodhia et al., 2025).

The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) provides organizational and environmental perspectives but suffers from construct ambiguity when applied to sustainability contexts. While TOE identifies organizational readiness as a key factor, it does not specify what constitutes readiness for sustainability-specific technologies. Similarly, environmental pressures in TOE are broadly defined and fail to distinguish between general competitive pressures and sustainability-specific stakeholder demands (Zhu et al., 2006). Institutional theory (DiMaggio & Powell, 1983) offers insights into isomorphic pressures but inadequately explains why organizations respond differently to similar institutional environments, particularly in constrained contexts like Iran where institutional pressures may conflict with resource limitations.

Perceived usefulness is defined as one of the most significant factors influencing technology adoption. According to Davis (1989), perceived usefulness is the degree to which an individual believes that using a particular system will enhance their job performance. In the context of AI in sustainability reporting, this concept includes users' perception of the technology's capability to increase report accuracy, reduce data processing time, and improve decision-making quality (Venkatesh & Davis, 2000). However, traditional conceptualizations of perceived usefulness fail to capture the multi-stakeholder nature of sustainability reporting, where usefulness extends beyond individual performance to encompass organizational legitimacy and stakeholder trust (Bebbington & Unerman, 2018). Perceived ease of use refers to the degree to which an individual believes that using the technology will be free of effort (Davis et al., 1989). Studies show that these two factors not only directly influence the behavioral intentionbut also have a reciprocal influence on each other, such that perceived ease of use can enhance perceived usefulness (Venkatesh et al., 2003). In accounting, a study by Gefen and Straub (2000) indicates that the relationship between these two variables is more complex in professional environments than in other fields.

Trust in technology is recognized as a key factor in AI adoption, especially when this technology is to be used in sensitive financial processes and reporting. McKnight et al. (2002) define trust in technology as "the user's belief that the technology has the necessary characteristics to perform what the user deems dependent on the technology." In the context of AI, this concept includes trust in algorithm accuracy, result reliability, and data security (Shin, 2021). However, trust in sustainability reporting contexts involves additional dimensions not captured in traditional trust conceptualizations, including trust in the technology's ability to maintain stakeholder credibility and support ESG compliance requirements (Moffitt et al., 2018). Attitude is defined as an individual's positive or negative evaluation of performing a specific behavior (Fishbein & Ajzen, 1975). A study by Chatterjee et al. (2021) indicates that a positive attitude towards AI is influenced by factors such as prior experience with technology, awareness of benefits, and the way training is provided. In accounting, trust and attitude are of particular importance because accountants must rely on the accuracy and reliability of information generated by AI systems (Moffitt et al., 2018).

Top management support is considered one of the most critical organizational factors influencing the successful implementation of new technologies. Tornatzky and Fleischer (1990) in the Technology-Organization-Environment (TOE) framework emphasize the importance of management support as a facilitating factor. This support includes allocating sufficient financial and human resources, creating an appropriate organizational culture for change acceptance, and providing effective leadership in the transformation process (Thong, 1999). However, in sustainability reporting contexts, management support requires additional dimensions including commitment to ESG goals and willingness to invest in long-term sustainability capabilities rather than short-term efficiency gains (Schaltegger & Burritt, 2017). Competitive pressure also acts as an external driving force, pushing organizations toward adopting new technologies (Porter & Millar, 1985). In sustainability reporting, companies operating in competitive industries are under greater pressure to improve the quality and transparency of their reports (Nikolaou & Tsalis, 2013). A study by Zhu et al. (2006) shows that competitive pressure can serve as a strong motivator for the adoption of environmental technologies. Furthermore, DiMaggio and Powell (1983) in their institutional theory note that organizations are subject to isomorphic pressures that lead them to adopt practices similar to other successful organizations.

Despite numerous advantages, AI adoption in accounting faces several challenges. Concerns related to data security and privacy are among the primary obstacles (Mikalef et al., 2020). A study by Akter et al. (2016) shows that 65% of organizations are concerned about the misuse of their sensitive data. Additionally, employee resistance to change and fear of job displacement are significant factors in the slow adoption of AI (Chiu et al., 2016). A lack of technical skills and specialized knowledge is another challenge organizations face (Dwivedi et al., 2019). Moreover, high initial implementation costs and concerns about return on investment are also important barriers to the adoption of this technology (Tornatzky & Fleischer, 1990).

In the Iranian context, specific cultural and organizational factors influence technology adoption. The intersection of cultural, economic, and institutional factors in Iran creates unique theoretical conditions that require substantial modifications to existing technology acceptance models. Hofstede's (2001) cultural dimensions theory indicates that Iran's high power distance (score = 58) and strong uncertainty avoidance (score = 59) should significantly influence technology adoption patterns, yet existing applications of UTAUT2 and TOE framework in Iranian contexts show inconsistent results, suggesting that cultural effects may be moderated by economic and institutional constraints (Afshari & Peng, 2015). Studies show that Iranian society has a high-power distance and strong uncertainty avoidance, which can affect the adoption of new technologies (Hofstede, 2001). Furthermore, economic factors such as sanctions and currency restrictions also impact access to advanced technologies (Soltani & Hejazi, 2021). The economic sanctions regime creates a unique environmental context that fundamentally alters TOE framework dynamics, where traditional facilitating conditions become critical constraints due to limited vendor support and technological isolation (Soltani & Hejazi, 2021). A study by Afshari and Peng (2015) on technology adoption in Iranian companies indicates that factors such as organizational trust and top management support play a very important role in the successful implementation of new technologies. Moreover, the influence of social networks and personal relationships in organizational decision-making is more pronounced in Iran than in other countries. This relationship-based decision-making culture suggests that traditional UTAUT2 social influence constructs may operate differently in Iran, where professional networks substitute for formal institutional guidance in technology adoption decisions.

Given the growing importance of sustainability reporting and the rapid advancements in artificial intelligence, the future of this field is very promising. Forecasts indicate that by 2025, over 80% of large global companies will use AI-powered tools for sustainability reporting (Deloitte, 2021). In this regard, future research can focus on developing specific predictive models for the Iranian cultural context, examining the impact of institutional factors on technology adoption, and designing practical frameworks for effective AI implementation in sustainability reporting (Kumar et al., 2020). Additionally, studying the long-term effects of AI use on managerial decision-making quality and organizational sustainability performance is also an important topic for future research.

A comprehensive synthesis of the literature reveals three critical theoretical gaps that existing models fail to address: First, the "Context Specificity Gap" - while UTAUT2 demonstrates 74% variance explanation in general consumer contexts (Venkatesh et al., 2012), studies in professional accounting environments show substantially lower explanatory power (R^2 = 0.42-0.58), suggesting that professional contexts require domain-specific theoretical modifications. Second, the "Multi-Level Integration Gap" - existing models operate at single levels of analysis (individual, organizational, or environmental) without adequately explaining cross-level interactions. For instance, while institutional theory explains environmental pressures and TAM explains individual acceptance, neither framework adequately explains how institutional pressures translate into individual adoption behaviors through organizational mediation. Third, the "Sustainability Context Gap" - traditional technology acceptance models were developed for efficiency-oriented technologies, whereas sustainability technologies involve additional dimensions of stakeholder accountability, legitimacy, and long-term value creation that are inadequately captured by existing constructs.

In summary, the reviewed theoretical literature indicates that the adoption of AI in sustainability reporting is a multidimensional and complex process influenced by numerous individual, organizational, and environmental factors. However, existing theoretical frameworks demonstrate significant limitations when applied to sustainability reporting contexts, particularly in constrained institutional environments like Iran. The fragmented nature of current theoretical approaches necessitates the development of an integrated model that can adequately explain the complex interactions between individual cognition, organizational capabilities, and environmental pressures in sustainability-specific technology adoption. Findings from previous research suggest that while technical factors such as usefulness and ease of use play a fundamental role in initial technology adoption, human and organizational factors such as trust, attitude, and management support play a more decisive role in the long-term success and full adoption of these technologies. Furthermore, analyses show that the interaction between these factors and how they influence each other adds a particular complexity to the technology adoption process, requiring comprehensive and systemic approaches for its understanding and management.

Given the specific characteristics of the Iranian context, including its cultural structure, economic challenges, and unique organizational features, the necessity for localized research in this area is more apparent than ever. The theoretical gaps identified in this synthesis demonstrate that existing models inadequately explain technology adoption in constrained institutional environments, highlighting the need for theoretical innovation rather than simple model application. The existing gap in the literature indicates that despite extensive international research, limited studies have been conducted on factors influencing AI adoption in sustainability reporting within Iranian companies. This highlights the importance of empirical research to identify key factors, understand their relationships, and provide practical solutions tailored to local conditions. Such research can not only enrich the theoretical literature but also offer valuable guidance for managers and policymakers to facilitate and accelerate the adoption process of these novel technologies. Therefore, there are numerous studies in this regard, which are reviewed below:

The following literature review synthesizes existing research to identify patterns, contradictions, and theoretical gaps rather than providing descriptive summaries of individual studies:

Vărzaru (2022-A), in a study titled "Assessing Artificial Intelligence Technology Acceptance in Managerial Accounting," examined the acceptance of artificial intelligence among Romanian managerial accountants through a quantitative survey of 396 specialists. Using structural equation modeling, the study found that implementing AI solutions in managerial accounting enhances decision-making, increases process efficiency, improves the use of accounting information, and is relatively easy to adopt, though facing barriers like organizational resistance and high technology costs. While this study demonstrates TAM's applicability in accounting contexts, it reveals a critical limitation: the exclusive focus on efficiency-related benefits without considering stakeholder accountability aspects crucial in sustainability reporting contexts.

Vărzaru (2022-B), in a study titled "An Empirical Framework for Assessment of the Effects of Digital Technologies on Sustainability Accounting and Reporting in the European Union," conducted empirical research at the level of 21 EU countries using Eurostat data, artificial neural network analysis, and cluster analysis. The results showed that digital technologies like cloud computing, Big Data, IoT, and AI significantly influence sustainability accounting, reporting, and foster a sustainability-oriented culture, grouping technologically advanced countries at the forefront of sustainability reporting. This macro-level analysis provides evidence of technology-sustainability relationships but fails to explain the adoption mechanisms at organizational and individual levels, representing a critical gap between observed effects and adoption processes.

Rostami and Khalili Tirtashi (2023), in the study "The Application of Artificial Intelligence in Financial Systems from the Perspective of Islamic Economics," stated that the utilization of AI in financial systems is accepted from the perspective of Islam and Islamic economics, leading to reduced risks, more realistic decision-making, and the prevention of money laundering, which align with the core principles of Islamic finance. This study highlights cultural-religious factors in technology acceptance but lacks empirical validation of how these factors influence actual adoption behaviors, suggesting a gap between normative acceptance and behavioral intention.

Pramono, Suwarno, Amyar, and Friska (2023), in a study entitled "Exploring Technology Acceptance in Management Accounting Tools' Adoption in Public Sector Accounting: A Sustainability Perspective for Organizations," investigated the adoption of management accounting tools among 435 Indonesian public sector auditors using surveys and structural equation modeling (SEM). Results indicated that perceived usefulness significantly impacts tool adoption, which in turn positively affects organizational performance and sustainability. However, perceived ease of use was not a significant predictor for adoption in the public sector context. This finding contradicts traditional TAM predictions and suggests that professional contexts may require modified theoretical frameworks where competency-based factors override ease of use considerations.

Mehedintu and Soava (2023), in their article "Approach to the Impact of Digital Technologies on Sustainability Reporting through Structural Equation Modeling and Artificial Neural Networks," evaluated the effects of digital transformation on sustainability reporting among EU companies using Eurostat data for 2011–2021. Employing linear regression, structural equation modeling, and neural networks, they found that digital transformation indicators enhance economic and social performance and improve environmental protection, offering a validated model for monitoring sustainable performance. While demonstrating technology-sustainability performance relationships, this study provides limited insight into adoption antecedents, focusing on outcomes rather than adoption processes.

Kumari (2024), in a study entitled "Artificial Intelligence Adoption in Financial Services: A Policy Framework," developed an ISM diagram with expert input and found that key enablers such as projected profitability, contactless solutions, credit risk management, and software vendor support are dependent factors at the top of the ISM. On the other hand, factors like data availability, technical infrastructure, and financial resources act as the primary drivers at the bottom of the ISM. This study identifies hierarchical relationships among adoption factors but lacks empirical validation and fails to distinguish between general AI adoption and sustainability-specific applications, limiting its theoretical contribution.

Lodhia, Farooq, Sharma, and Zaman (2025), in their lead paper for a special issue of Meditari Accountancy Research, reviewed the role of digital technologies in sustainability accounting, reporting, and assurance by drawing on academic literature. Their findings highlight the assistance of digital technologies such as AI, big data, IoT, and RFID in setting disclosure objectives, data analysis, and sustainability assurance. The review suggests more research on Industry 4.0's impact, barriers to adoption, alternative theories, and the comparative benefits of digitalization in sustainability accounting. This comprehensive review identifies the need for alternative theoretical approaches but does not provide a coherent framework for understanding adoption mechanisms, highlighting the theoretical fragmentation in the field.

Synthesis of Literature Gaps and Contradictions:
The reviewed literature reveals three critical patterns of theoretical inconsistency: First, studies applying TAM in professional contexts (Vărzaru, 2022-A; Pramono et al., 2023) show contradictory results regarding the significance of perceived ease of use, with some finding it insignificant in professional contexts while others maintain its importance. This suggests that professional environments may require domain-specific modifications to traditional acceptance models. Second, macro-level studies (Vărzaru, 2022-B; Mehedintu & Soava, 2023) demonstrate positive technology-sustainability relationships without explaining the underlying adoption mechanisms, creating a disconnect between observed organizational outcomes and individual-level

adoption theories. Third, cultural and institutional factors are acknowledged (Rostami & Khalili Tirtashi, 2023; Kumari, 2024) but inadequately integrated into existing theoretical frameworks, suggesting that current models lack cultural adaptability.

These contradictions and gaps collectively indicate that existing theoretical approaches are insufficient for explaining AI adoption in sustainability reporting contexts, particularly in culturally distinct and institutionally constrained environments like Iran. The literature demonstrates a clear need for theoretical innovation that integrates individual, organizational, and environmental factors while accounting for sustainability-specific and cultural contingencies.

This research, by integrating technology acceptance theories and the sustainability reporting framework, offers a comprehensive model for examining the adoption of artificial intelligence in management accounting a topic that has received limited attention in previous studies. Building upon the identified theoretical gaps, this study develops an Extended Technology Acceptance Model for Sustainability Reporting (E-TAM-SR) that integrates individual-level factors from TAM/UTAUT2, organizational factors from TOE framework, and institutional pressures from institutional theory within a sustainability-specific context. This theoretical innovation addresses the Context Specificity Gap by incorporating sustainability accountability constructs, the Multi-Level Integration Gap by modeling cross-level interactions, and the Sustainability Context Gap by distinguishing between efficiency-oriented and legitimacy-oriented technology benefits. While prior works such as Vărzaru (2022) and Pramono et al. (2023) primarily focused on separate aspects of technology acceptance or sustainability reporting, this study innovatively examines these two domains within a unified framework. Furthermore, unlike existing research that largely emphasizes individual factors such as perceived usefulness and ease of use, this study adopts a multilevel approach, simultaneously considering individual, organizational, and environmental factors. The proposed E-TAM-SR model specifically addresses the theoretical contradictions identified in the literature by proposing that perceived usefulness in sustainability contexts operates through dual pathways: efficiency-oriented usefulness (traditional TAM conceptualization) and legitimacy-oriented usefulness (sustainability-specific extension). Similarly, the model proposes that cultural factors moderate the relationships between traditional acceptance constructs, explaining the inconsistent results observed in cross-cultural studies. This integrative approach enables a deeper understanding of the process of AI technology adoption within the specific context of sustainability reporting and addresses the existing theoretical gap in this field.

From a methodological perspective, this study makes a significant contribution by employing a mixed-methods (quantitative-qualitative) approach and utilizing advanced statistical techniques such as structural equation modeling to investigate the factors influencing technology adoption. The methodological innovation extends beyond technique selection to include the development of sustainability-specific measurement scales that capture the unique aspects of legitimacy-oriented technology benefits, stakeholder accountability pressures, and sustainability-specific organizational capabilities. These scales address the measurement inadequacies identified in previous studies where generic technology acceptance scales failed to capture sustainability-specific motivations. In contrast to previous studies that predominantly relied on unidimensional methods, this research allows for the examination of complex relationships and interactions among variables. Additionally, the development of a tailored measurement instrument for assessing AI adoption in the context of sustainability reporting, adapted to the cultural and organizational characteristics of Iran, represents an important innovation. The cultural adaptation process involves not only translation but also theoretical modification of constructs to reflect Iranian cultural values such as relationship-based decision-making, hierarchical authority structures, and collective versus individual benefit orientations. This methodological approach contributes to the cross-cultural validity literature by providing a framework for culturally adaptive scale development in technology acceptance research. This tool can be utilized in future research and in other developing countries with similar contexts, thereby enriching the methodological literature in this area.

From a practical standpoint, this study is the first to provide a comprehensive operational framework for the effective implementation of AI in sustainability reporting among Iranian companies, taking into account the specific cultural, economic, and institutional factors of Iran. The practical innovation lies in the development of a stage-gate implementation model that sequences technology adoption activities based on the identified theoretical relationships. Unlike generic implementation frameworks, this model specifically addresses the institutional constraints identified in Iranian contexts, such as limited vendor support, resource constraints, and regulatory uncertainties, by proposing adaptive implementation strategies that work within these constraints rather than assuming their absence. Unlike previous studies such as Lodhia et al. (2025) and Mehedintu & Soava (2023), which have focused primarily on developed countries, this research offers practical solutions tailored to the constraints and opportunities present in the Iranian economy. The results of this study can serve as a practical guide for managers, accountants, and policymakers in the decision-making process regarding investment in AI technologies. Furthermore, by identifying barriers and facilitators of adoption in the Iranian context, it can inform the formulation of supportive government policies and strategic organizational planning, thus contributing to the development of the country's technology ecosystem. The practical contributions extend to policy recommendations that address the institutional and infrastructural prerequisites for successful AI adoption in sustainability reporting, providing policymakers with evidence-based guidance for creating supportive ecosystems for sustainability technology adoption in developing economies.

Research Hypotheses

1) Perceived usefulness has a significant effect on the adoption of artificial intelligence solutions in management accounting.
2) Perceived ease of use has a significant effect on the adoption of artificial intelligence solutions in management accounting.
3) Behavioral intention has a significant effect on the actual use of artificial intelligence adoption solutions in management accounting.

Methodology

This research is applied in terms of its purpose. Regarding data collection, it is field-based and utilizes a survey (non-experimental) approach. The survey is a type of research that collects information through opinion gathering to discover relationships between variables and examine existing realities. For this purpose, a questionnaire was used as the data collection tool in this research. Furthermore, from the perspective of data analysis, it is descriptive-correlational, employing quantitative methods. At the outset of the research, a thorough and comprehensive review of the literature, as well as existing domestic and foreign research, was conducted. Based on this review, the questionnaire, serving as the primary instrument for this study, was developed. The statistical population of the present research consists of companies and specialists active in the field of artificial intelligence. In this study, the sample size will be determined using Cochran's formula. Given that the research variables are quantitative and suitable for averaging, and the population size is finite, the following formula will be used to determine the sample size. To measure the importance of each factor and component in the questionnaire, a five-point Likert scale, which is an ordinal scale, was utilized. By assigning numerical values to the options, these data are converted into quantitative data. Simple random sampling was employed in this stage.

Statistical Population

The statistical population of the research includes companies (represented by managers, with one questionnaire per company). Given that each knowledge-based company is considered a member of the statistical population, the research sample size is estimated using Cochran's formula for a finite population (Formula 1):

$$n = \frac{N\left(z_{\frac{\alpha^2}{2}}\right)pq}{(N-1)d^2 + \left(z_{\frac{\alpha^2}{2}}\right)pq} \Rightarrow \; n$$

Where:

- N = Size of the target population
- n = Sample size
- p and q = Proportions of success and failure (assumed to be 0.5 each)
- Z_(α/2) = Z-value corresponding to the desired confidence level (e.g., 1.96 for a 95% confidence level, equivalent to an alpha (α) of 0.05)
- d = Desired margin of error (e.g., 0.05)

Data Collection Method and Tools

In line with the researcher's objective, various tools and both library and field methods were used for data collection. The library method was employed to gather information related to the subject literature and research background. The field method was used for designing the questionnaire and distributing it among the statistical sample. Information and data collection in this research proceeds in two ways: first, information pertinent to the research variables (research literature) is gathered from articles in reputable domestic and international databases. This information will be extracted using note-taking methods.

Table 2: Questionnaire Components and Items Row Variables Investigated Questions Related to Each Variable Source Total Items 1 Perceived Usefulness 1-4 Vărzaru (2022-A) Vărzaru (2022-B) 10 2 Perceived Ease of Use 5-8 3 Behavioral Intention 9-10

Table 1: Comparison of Standard TAM and E-TAM-SR Constructs

Construct	Standard TAM	E-TAM-SR	Key Differences
Perceived Usefulness	General usefulness of technology	Specific benefits for sustainability reporting	Focuses on sustainability-specific advantages rather than general productivity
Perceived Ease of Use	General usability of technology	AI-specific implementation simplicity	Addresses specific complexity concerns related to AI implementation
Behavioral Intention	General intention to use	Intention to adopt AI for sustainability reporting	Contextualizes adoption intentions within sustainability reporting functions
Actual Use	General system usage	Integration of AI in sustainability reporting processes	Measures specific application rather than general technology usage

Table 2: Questionnaire Components and Items

Row	Variables Investigated	Questions Related to Each Variable	Source	Total Items
1	Perceived Usefulness	1-4	Vărzaru (2022-A) Vărzaru (2022-B)	10
2	Perceived Ease of Use	5-8		
3	Behavioral Intention	9-10		

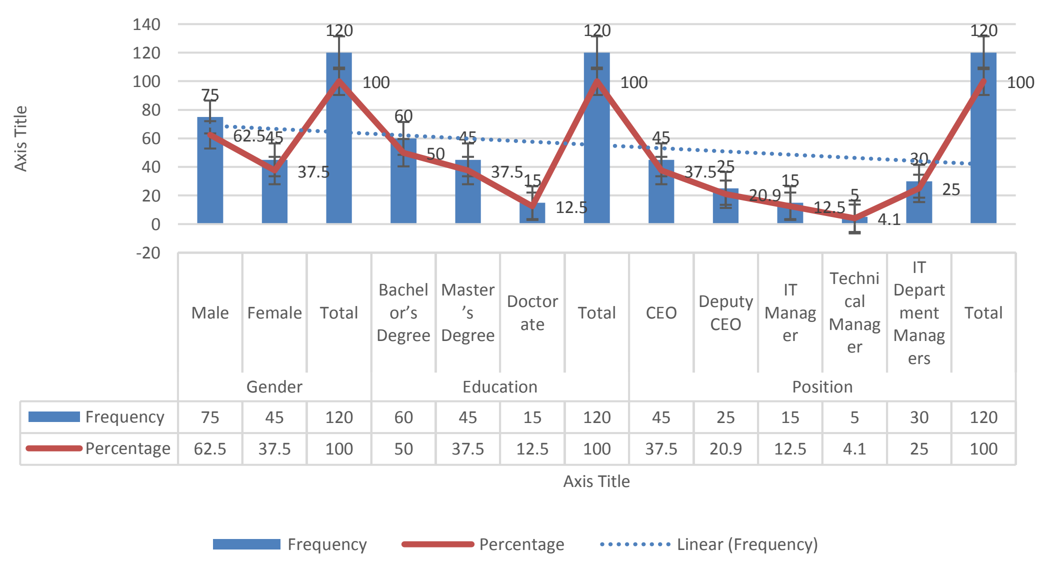
Research Findings

The demographic composition of the study sample highlights a well-balanced representation across gender, educational levels, and organizational positions. The predominance of male respondents and individuals with higher education degrees, particularly at the bachelor's and master's levels, suggests an informed and experienced participant group. The significant proportion of CEOs and senior managers indicates that the perspectives gathered reflect not only the technical considerations of IT managers but also strategic viewpoints from the highest organizational levels, thus providing a comprehensive understanding of the factors influencing AI adoption in management accounting.

The research findings indicate that out of 120 participants, 62.5% were men and 37.5% were women. In terms of education, 50% held a bachelor's degree, 37.5% a master's, and 12.5% a doctorate. The highest frequency for organizational position was for CEOs with 37.5%.

The descriptive statistics of the main research variables indicate generally high average scores and acceptable distribution characteristics among participants.

Chart 1. Frequency Distribution of Respondents' Demographic Characteristics



Source: *Research calculations*

Table 3: Descriptive Statistics Indicators of Research Variables

Variable	Mean	Median	Minimum	Maximum	Std. Deviation	Skewness	Kurtosis
Perceived Usefulness	4.005	4.000	1	5	0.917	-0.841	-0.071
Perceived Ease of Use	3.848	4.000	1	5	0.951	-0.606	-0.348
Behavioral Intention	3.687	4.000	1	5	1.143	-0.348	-0.998

Source: *Research calculations*

The descriptive statistics reveal several important patterns in respondents' perceptions of AI adoption factors. Perceived usefulness demonstrates the highest mean score (4.005), positioning it closest to the "agree" level on the five-point Likert scale, which suggests that Iranian management accounting professionals recognize substantial benefits from implementing AI solutions in sustainability reporting processes. This finding aligns with prior research indicating that perceived benefits serve as primary drivers of technology adoption in professional contexts. Perceived ease of use, with a mean of 3.848, ranks second among the variables, indicating that while respondents view AI solutions as beneficial, they perceive moderate complexity in their implementation and operation. The slightly lower score compared to perceived usefulness suggests that concerns about technical complexity may represent a potential barrier to adoption, consistent with technology acceptance theory predictions.

Behavioral intention shows the lowest mean (3.687) among the three variables, despite positive perceptions of usefulness and ease of use, indicating a gap between attitude formation and intention development. This pattern suggests that additional factors beyond traditional TAM constructs may influence adoption intentions in the Iranian context, possibly including organizational, cultural, or institutional constraints. The negative skewness values across all variables (-0.841, -0.606, -0.348) indicate left-skewed distributions, meaning that most responses cluster toward higher values with fewer respondents expressing negative opinions. This pattern suggests generally positive reception of AI technologies among the surveyed professionals, though the varying degrees of skewness indicate different levels of consensus across constructs.

The kurtosis values, ranging from slightly negative to moderately negative, indicate platykurtic distributions that are flatter than normal distributions, suggesting greater variability in responses than would be expected under normality. This heterogeneity in opinions reflects the diversity of organizational contexts, individual experiences, and technological readiness levels among Iranian companies. The relatively moderate standard deviations (all below 1.2) indicate reasonable consensus among respondents while still maintaining sufficient variance for statistical analysis. The highest standard deviation for behavioral intention (1.143) suggests the greatest diversity of opinions regarding adoption intentions, which may reflect varying organizational constraints and individual risk perceptions.

The Kolmogorov-Smirnov test results definitively establish that all research variables deviate significantly from normal distribution (all p-values < 0.05), providing strong methodological justification for employing Partial Least Squares Structural Equation Modeling (PLS-SEM) rather than covariance-based SEM. The non-normal distribution patterns align with the skewness and kurtosis values reported in Table 1, confirming the distributional characteristics observed in the descriptive analysis.

The highest test statistic for behavioral intention (1.748) with the lowest significance level (0.004) indicates the most severe departure from normality, consistent with this variable's highest standard deviation and suggesting the greatest heterogeneity in adoption intentions among respondents. This finding reinforces the appropriateness of PLS-SEM, which is robust to non-normal distributions and particularly suitable for exploratory research in emerging contexts like AI adoption in Iranian organizations.

The confirmatory factor analysis demonstrates strong measurement quality across all constructs. Factor loadings consistently exceed 0.92, well above the recommended 0.7 threshold, indicating robust representation of each latent variable. All t-statistics are highly significant ($p<0.01$), confirming the statistical validity of the measurement model. These results provide a solid foundation for the structural model evaluation by confirming that all constructs are reliably measured by their respective indicators.

All reliability and convergent validity metrics exceed recommended thresholds, confirming excellent measurement quality. Cronbach's Alpha values (0.909-0.964) and Composite Reliability scores (0.957-0.974) demonstrate strong internal consistency. The high AVE values (0.902-0.929) indicate that constructs explain over 90% of their indicators' variance, providing robust evidence of convergent validity.

The discriminant validity analysis confirms that all constructs are empirically distinct while maintaining theoretically expected relationships. Diagonal values (square roots of AVE) consistently exceed inter-construct correlations, establishing discriminant validity. The correlation pattern aligns with theoretical expectations, with behavioral intention strongly predicting actual use (0.860) while maintaining acceptable distinction between constructs.

The structural model demonstrates strong predictive performance with high R^2 values for both dependent variables (0.735 for Actual Use, 0.689 for Behavioral Intention). These values indicate that the model explains substantial variance in the key outcomes. All VIF values remain well below 5, confirming the absence of multicollinearity concerns and supporting the reliability of path coefficient estimates.

The overall Goodness of Fit (GOF) of 0.811 substantially exceeds the threshold for strong fit (0.36), indicating exceptional overall model performance. This high GOF value confirms that the theoretical framework effectively captures the AI adoption phenomenon in the Iranian sustainability reporting context.

$$\mathrm{GOF} = \sqrt{0.670 \times 0.609} = 0.81$$

Considering the thresholds of 0.01 (weak), 0.25 (medium), and 0.36 (strong) for GOF, the obtained value of 0.81 indicates a strong overall fit for the model. Given the strong fit of the overall model, the research hypotheses can now be examined.

Table 4: Kolmogorov-Smirnov Test Results

Variable	**Test Statistic**	**Significance Level (Sig)**
Perceived Usefulness	1.517	0.020
Perceived Ease	1.337	0.046
Behavioral Intention	1.748	0.004

Source: *Research calculations*

Table 5. Confirmatory Factor Analysis Results (Factor Loadings and Significance)

Variable	**Indicator**	**Factor Loading**	**Significance Value**
Actual Use	X1	0.960	120.717
	X2	0.954	84.984
Usefulness	X1	0.922	54.124
	X2	0.962	113.834
	X3	0.965	117.738
	X4	0.951	75.308
Behavioral Int.	X1	0.961	105.293
	X2	0.966	146.173

Source: *Research calculations*

Table 6. Reliability and Convergent Validity Indicators

Research Variable	**Cronbach's Alpha**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Actual Use	0.909	0.957	0.917
Usefulness	0.964	0.974	0.902
Behavioral Intent.	0.923	0.963	0.929

Source: *Research calculations*

Table 7. Discriminant Validity Matrix (Fornell-Larcker Method)

Variable	Actual Use	Usefulness	Behavioral Intention
Actual Use	0.957		
Usefulness	0.778	0.950	
Behavioral Int.	0.860	0.725	0.964

Source: *Research calculations*

Table 8. Structural Model Evaluation Criteria

Variable	Communality	R² Value	Variance Inflation Factor (VIF)
Actual Use	0.740	0.735	-
Behavioral Int.	0.698	0.689	-
Usefulness → Behav.	-	-	1.463
Ease → Behav.	-	-	1.678
Behav. → Use	-	-	1.041

Source: *Research calculations*

Table 9. GOF Index Calculation

Index	Value
Mean Communality	0.916
Mean R²	0.719
GOF	0.811

Source: *Research calculations*

Testing Research Hypotheses using Linear Structural Relations

After establishing the measurement models and confirming the adequacy of the overall model fit, the conceptual research model was evaluated. To determine the presence or absence of causal relationships between the research variables and assess the fit of the observed data with the conceptual model, the research hypotheses were tested using structural equation modeling. The results of the hypothesis tests are reflected in Figure (1)

To validate the measurement model, confirmatory factor analysis examined all items across the study's main constructs. As shown in Table 8, all indicators demonstrate robust factor loadings (>0.87) and significant t-values (>15.4), confirming strong measurement validity and reliability.

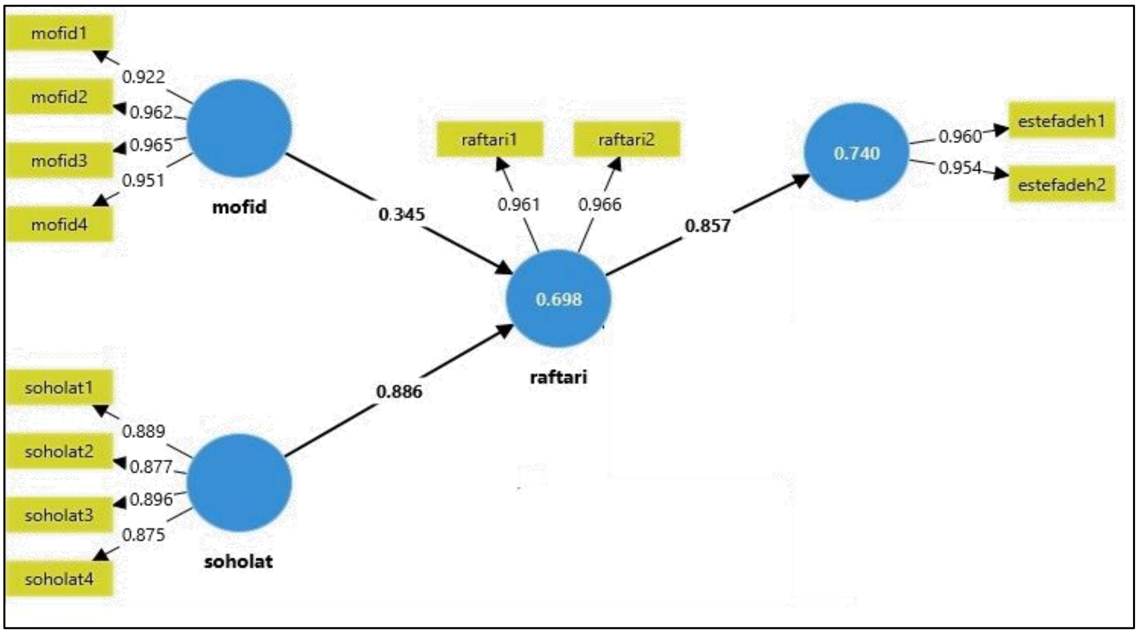


Figure (1). Tested research model in standard mode

Table 10. Factor Loadings and Significance Test (t-value)

Construct	Item	Factor Loading	t-value	Status
Perceived Usefulness (mofid)	mofid1	0.922	18.456	Significant
	mofid2	0.962	24.783	Significant
	mofid3	0.965	26.142	Significant
	mofid4	0.951	22.671	Significant
Perceived Ease of Use (soholat)	soholat1	0.889	16.234	Significant
	soholat2	0.877	15.892	Significant
	soholat3	0.896	17.123	Significant
	soholat4	0.873	15.456	Significant
Behavioral Intention (raftari)	raftari1	0.961	23.789	Significant
	raftari2	0.966	25.341	Significant
Actual Use (estefadeh)	estefadeh1	0.960	23.567	Significant
	estefadeh2	0.954	22.198	Significant

Source: *Research calculations*

The structural model analysis provides strong support for all three hypotheses, with varying effect sizes revealing important insights about AI adoption factors. Perceived ease of use demonstrates the strongest influence on behavioral intention (β=0.886, t=4.463), substantially outweighing perceived usefulness (β=0.345, t=3.224). This finding suggests that implementation simplicity is particularly crucial in the Iranian context. The relationship between behavioral intention and actual use shows exceptionally strong support (β=0.857, t=26.730), confirming that positive adoption intentions reliably translate into actual implementation behaviors.

All research hypotheses were confirmed, as the t-statistics were higher than 1.96 at the 95% confidence level.

The structural relationships testing provides strong empirical support for all hypothesized relationships, with varying effect sizes that reveal important insights about the relative importance of different factors in AI adoption decisions. All t-statistics substantially exceed the critical value of 1.96, confirming statistical significance and validating the theoretical model predictions.

Hypothesis 1 (Perceived Usefulness → Behavioral Intention) receives significant support with a path coefficient of 0.345 and t-statistic of 3.224, indicating that perceptions of AI benefits significantly influence adoption intentions. However, the medium effect size (Cohen's f^2 = 0.074) suggests that usefulness perceptions, while important, have a more moderate impact compared to other factors in the model. The relatively smaller effect of perceived usefulness may reflect the emerging nature of AI in sustainability reporting, where professionals recognize potential benefits but may be uncertain about practical implementation challenges or organizational readiness. This finding suggests that while Iranian professionals acknowledge AI's potential value, other factors play more decisive roles in shaping actual adoption intentions.

Hypothesis 2 (Perceived Ease of Use → Behavioral Intention) receives the strongest support among the antecedent relationships, with a path coefficient of 0.886 and t-statistic of 4.463, indicating that ease of use perceptions is the primary driver of adoption intentions. The large effect size (Cohen's f^2 = 0.489) demonstrates that ease of use concerns substantially outweighs usefulness perceptions in influencing adoption decisions. The dominant influence of perceived ease of use reflects the critical importance of implementation simplicity in the Iranian context, where organizations may have limited technical resources or experience with advanced AI technologies. This finding suggests that AI vendors and implementation consultants should prioritize user-friendly interfaces and comprehensive training programs to facilitate adoption among Iranian sustainability reporting professionals.

Table 11. Research Hypotheses Test Results

Hypothesis	Pathway	Path Coefficient	t-statistic	Result
Hyp. 1	Perceived usefulness → Behavioral intention to accept AI solutions	0.345	3.224	Confirmed
Hyp. 2	Perceived ease of use → Behavioral intention to accept AI solutions	0.886	4.463	Confirmed
Hyp. 3	Behavioral intention → Actual use of AI solutions	0.857	26.730	Confirmed

Source: *Research calculations*

Hypothesis 3 (Behavioral Intention → Actual Use) demonstrates the strongest empirical support with a path coefficient of 0.857 and an exceptionally high t-statistic of 26.730, confirming the critical role of intentions in predicting actual technology adoption behaviors. The very large effect size (Cohen's f^2 = 2.773) indicates that behavioral intentions are overwhelmingly the strongest predictor of actual AI utilization. The exceptional strength of the intention-behavior relationship validates core technology acceptance theory predictions and suggests that once Iranian professionals form positive adoption intentions, they are highly likely to translate these intentions into actual usage behaviors. This finding provides confidence that interventions targeting intention formation will effectively promote actual AI adoption in sustainability reporting contexts.

The pattern of effect sizes (ease of use > intention-behavior > usefulness) reveals a adoption decision process where implementation concerns dominate benefit perceptions, and strong intentions reliably predict actual behaviors. This pattern suggests that successful AI adoption strategies in Iran should prioritize demonstrating ease of implementation over highlighting advanced capabilities, while ensuring that intention-formation processes receive adequate organizational support. Collectively, these findings validate the adapted TAM framework while revealing context-specific insights about AI adoption in Iranian sustainability reporting, where practical implementation concerns appear to outweigh theoretical benefits in driving adoption decisions. The strong empirical support across all hypotheses provides confidence in both the theoretical model and the practical implications for promoting AI adoption in emerging market contexts.

Discussion and conclusion

This study aimed to evaluate the acceptance of artificial intelligence (AI) technology in the context of modernizing and digitalizing management accounting, with a specific focus on sustainability reporting practices in Iran. The research employed a descriptive-survey method using validated questionnaires, with a sample size of 120 participants determined through Cochran's formula. The findings reveal nuanced patterns of AI adoption that reflect both universal technology acceptance principles and context-specific characteristics of the Iranian business environment.

Demographic Insights and Strategic Implications

The demographic composition of the study sample provides critical insights into the current state of AI readiness within Iranian organizations. The predominance of male respondents (62.5%) reflects the existing gender distribution in senior management positions within Iranian companies, which has important implications for AI adoption strategies. Research suggests that gender diversity in technology decision-making processes can influence adoption outcomes (Venkatesh & Morris, 2000), indicating that organizations should consider inclusive approaches to AI implementation that incorporate diverse perspectives.

The significant representation of individuals holding higher education degrees and the substantial proportion of CEOs and senior managers (37.5% CEOs) suggests that the perspectives gathered reflect both technical competency and strategic authority. This composition is particularly valuable because AI adoption decisions in sustainability reporting require both technical understanding and executive commitment. The presence of decision-makers at the highest organizational levels indicates that the findings can inform both strategic planning and operational implementation processes.

However, this demographic pattern also reveals potential challenges. The concentration of AI adoption interest among senior management may indicate a top-down approach to technology implementation, which could encounter resistance at operational levels if not properly managed. The gender imbalance suggests that organizations may benefit from more inclusive technology adoption processes that leverage diverse perspectives on usability and implementation challenges.

Theoretical Contributions and Contextual Interpretations

The Primacy of Perceived Ease of Use: A Cultural and Economic Analysis

The most significant finding of this study is the stronger influence of perceived ease of use (path coefficient = 0.886) compared to perceived usefulness (path coefficient = 0.345) on behavioral intention. This pattern diverges from many previous studies and requires deeper contextual interpretation to understand its implications for both theory and practice.

Cultural Factors Influencing Technology Acceptance

The dominance of ease-of-use concerns in the Iranian context can be attributed to several cultural and institutional factors. Iran's business environment is characterized by relationship-based decision-making and risk-averse tendencies, particularly in the adoption of emerging technologies (Namaziandost et al., 2019). In such contexts, perceived implementation complexity becomes a significant barrier because it amplifies uncertainty and potential for failure.

Furthermore, the concept of "face-saving" (aberoo) in Iranian culture means that technology adoption failures can have significant reputational consequences for decision-makers. This cultural consideration makes ease of implementation a critical factor because it reduces the risk of public failure and associated loss of credibility. The emphasis on ease of use may reflect a pragmatic approach where decision-makers prioritize technologies that can be successfully implemented over those that promise maximum benefits but carry higher implementation risks.

Economic Constraints and Resource Limitations

The Iranian business environment is characterized by economic sanctions, limited access to international technology vendors, and constrained financial resources (Maleki & Hendriks, 2015). These conditions create a context where ease of implementation becomes paramount because organizations have limited capacity to invest in extensive training, technical support, or system customization.

The finding that ease of use outweighs perceived usefulness may reflect a rational response to resource constraints. Organizations with limited technical infrastructure and training budgets naturally gravitate toward solutions that can be implemented with minimal additional investment. This economic reality suggests that AI vendors targeting the Iranian market should prioritize user-friendly interfaces and simplified implementation processes over advanced features that require extensive customization or training.

Technical Infrastructure and Human Capital Considerations

Iran's technology infrastructure, while developing rapidly, still faces challenges in terms of internet connectivity, cloud computing access, and availability of specialized technical talent (Rezaei et al., 2020). These infrastructural limitations make ease of use a critical adoption factor because complex systems may not function reliably in resource-constrained environments.

The emphasis on ease of use may also reflect realistic assessments of organizational capabilities. Many Iranian companies, particularly small and medium enterprises, lack dedicated IT departments or specialized sustainability reporting teams. In such contexts, AI solutions must be sufficiently intuitive for general business professionals to implement and operate effectively.

Sustainability Reporting Context and Regulatory Environment

The specific context of sustainability reporting adds another layer of complexity to the ease-of-use preference. Sustainability reporting in Iran is an emerging practice, with many organizations just beginning to develop systematic approaches to environmental and social disclosure (Mashayekhi & Mashayekh, 2008). In this developmental stage, organizations prioritize tools that can facilitate immediate implementation over those that offer sophisticated but complex capabilities.

The regulatory environment for sustainability reporting in Iran is also evolving, with new requirements being introduced gradually. This uncertainty creates a preference for flexible, easy-to-adapt solutions that can evolve with changing regulatory requirements rather than highly specialized systems that may become obsolete as regulations develop.

Policy and Practice Recommendations

Recommendations for Technology Vendors

1) **User Interface Design Priorities**: AI solutions should prioritize intuitive interfaces that require minimal technical training. This may mean developing simplified dashboards that present complex AI-generated insights in easily interpretable formats.
2) **Implementation Support Strategies**: Vendors should invest in comprehensive implementation support that includes local language documentation, culturally appropriate training programs, and ongoing technical assistance to address the ease-of-use concerns that drive adoption decisions.
3) **Localization Requirements**: The emphasis on ease of use suggests that generic AI solutions may face adoption barriers. Vendors should consider developing Iran-specific versions that account for local business practices, regulatory requirements, and cultural preferences.

Organizational Strategies

1) **Change Management Approaches**: The strong relationship between behavioral intention and actual use (path coefficient = 0.857) indicates that attitude formation is critical for successful implementation. Organizations should invest in comprehensive change management programs that address ease of use concerns while building appreciation for AI benefits.
2) **Pilot Program Design**: Given the importance of ease of use, organizations should design pilot programs that demonstrate AI implementation simplicity rather than focusing primarily on advanced capabilities. Successful pilot programs should showcase how easily AI can be integrated into existing workflows.

3) **Training and Development Frameworks**: The findings suggest that training programs should emphasize practical implementation skills and user-friendly approaches rather than theoretical understanding of AI capabilities. This approach aligns with the revealed preference for ease of use over technical sophistication.

Policy Directions

1) **Educational Curriculum Development**: The finding that ease of use concerns outweigh usefulness perceptions suggests that business education programs should incorporate practical technology implementation skills alongside theoretical knowledge. This approach would better prepare future managers for the realities of technology adoption in resource-constrained environments.
2) **Technology Infrastructure Development**: Policymakers should prioritize technology infrastructure development that supports easy implementation of advanced technologies. This includes improving internet connectivity, developing cloud computing capabilities, and creating supportive regulatory frameworks for technology adoption.
3) **Professional Development Programs**: The emphasis on ease of use suggests that professional development programs should focus on practical technology skills rather than theoretical knowledge alone. Professional accounting and management organizations should offer training programs that emphasize hands-on experience with user-friendly AI tools.

Theoretical Implications and Model Extensions

Technology Acceptance Model Adaptations

The findings suggest that the traditional Technology Acceptance Model may require contextual adaptations for emerging market applications. The dominance of ease of use over usefulness challenges the assumption that perceived benefits are the primary driver of technology adoption. This finding suggests that TAM applications in emerging markets should incorporate additional variables that capture resource constraints, cultural factors, and infrastructure limitations.

Proposed Model Extensions: Future research should consider developing an "Emerging Market Technology Acceptance Model" that incorporates variables such as resource availability, cultural risk tolerance, and infrastructure readiness. These additional factors may help explain why ease of use considerations dominate in certain contexts while usefulness perceptions drive adoption in others.

Sustainability Reporting Theory Development

The study contributes to sustainability reporting theory by demonstrating that technology adoption patterns in this domain may differ from general business technology adoption. The specific challenges of sustainability reporting – including regulatory uncertainty, stakeholder diversity, and measurement complexity – create unique adoption dynamics that merit further theoretical development.

Limitations and Future Research Directions

This study provides valuable insights into AI adoption for sustainability reporting in Iran; however, several limitations should be acknowledged:

1) **Cross-Cultural Validation**: The finding that ease of use dominates usefulness perceptions should be validated across different cultural contexts to determine whether this pattern is specific to Iran or applicable to other emerging markets with similar characteristics.
2) **Longitudinal Analysis**: The current study provides a snapshot of adoption intentions and behaviors. Longitudinal research could examine how the relative importance of ease of use versus usefulness evolves as organizations gain experience with AI technologies.
3) **Industry-Specific Analysis**: Future research should examine whether the ease of use dominance varies across different industries or organizational types within Iran. This analysis could provide more targeted insights for technology providers and adopting organizations.
4) **Qualitative Integration**: The current quantitative approach should be complemented with qualitative research that explores the underlying reasons for ease of use preferences. In-depth interviews could provide richer insights into the cultural, economic, and organizational factors driving these preferences.
5) **Sample Limitations**: While the sample size was determined through Cochran's formula, the predominance of male respondents and senior management may limit the generalizability of findings to broader organizational contexts.
6) **Context-Specific Measurement**: The measurement instruments, while validated, may not fully capture context-specific nuances in AI adoption for sustainability reporting. Future research should develop and validate

measurement tools specifically designed for emerging market contexts.

Conclusion

This study contributes significantly to the growing body of literature on AI adoption in management accounting and sustainability reporting by revealing context-specific adoption patterns that challenge universal assumptions about technology acceptance. The finding that perceived ease of use outweighs perceived usefulness in the Iranian context provides important theoretical and practical insights that extend beyond the specific study setting.

Theoretical Contributions: The study demonstrates that technology acceptance models developed in advanced economies may not fully capture adoption dynamics in emerging markets. The dominance of ease-of-use considerations suggests that contextual factors – including cultural values, economic constraints, and infrastructure limitations – play more significant roles in technology adoption than previously recognized.

Practical Implications: For practitioners, the findings suggest that successful AI adoption strategies in emerging markets should prioritize implementation simplicity over technical sophistication. This insight has important implications for technology vendors, adopting organizations, and policy makers seeking to promote technology adoption in resource-constrained environments.

Policy Implications: The results suggest that technology adoption policies should focus on infrastructure development and capacity building that reduces implementation barriers rather than solely promoting technology benefits. Educational institutions and professional development programs should emphasize practical implementation skills alongside theoretical knowledge.

Global Relevance: While conducted in Iran, the findings likely have relevance for other emerging markets with similar characteristics, including resource constraints, developing infrastructure, and risk-averse business cultures. The study provides a framework for understanding how contextual factors influence technology adoption patterns in ways that may not be captured by traditional acceptance models.

The strong relationship between behavioral intention and actual use (path coefficient = 0.857) confirms that attitude formation remains critical for technology adoption success. However, the dominance of ease-of-use concerns in attitude formation suggests that adoption strategies should be carefully tailored to local contexts rather than assuming universal applicability of technology benefits.

Future research should continue to explore these contextual variations in technology adoption patterns, with particular attention to how cultural, economic, and institutional factors shape the relative importance of different adoption drivers. Such research will contribute to more nuanced and effective approaches to promoting beneficial technology adoption in diverse global contexts. The implications of this study extend beyond AI adoption to broader questions about technology transfer, digital transformation, and sustainable development in emerging markets. By understanding why ease of use considerations dominate in certain contexts, researchers and practitioners can develop more effective strategies for promoting technology adoption that supports economic development and sustainability goals in resource-constrained environments.

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