Information Technology Adoption Model in the Auditing Profession with a Sustainable Development Approach

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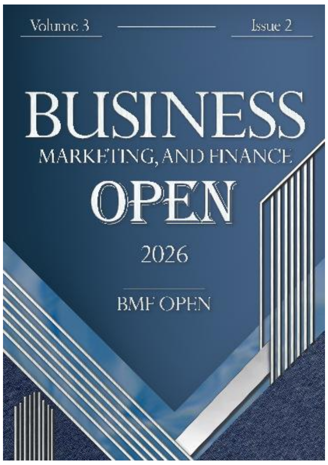

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Abstract: This study aims to develop a model for information technology (IT) adoption in the auditing profession, aligned with the principles of sustainable development. The study was conducted over a six-month period, from March to August 2025, to ensure a comprehensive data collection and analysis process. A mixed-methods approach was employed, combining qualitative interviews with quantitative analysis. In the first phase, semi-structured interviews were conducted with 12 auditing experts and analyzed through thematic coding, resulting in the identification of 77 key indicators. These indicators were refined using the fuzzy Delphi method, confirming expert consensus. A structured questionnaire was then developed based on the finalized indicators and distributed among auditors in publicly listed companies. Structural equation modeling (SEM) using Smart PLS was applied to validate the model. The results identified 12 core dimensions influencing IT adoption in auditing: Big Data, Analysis and Prediction, Software Utility, Specialized Human Resources, Data Security, Environmental Considerations, Improved Efficiency, Enhanced Analytical Depth, Better Decision Making, Enhanced Auditor Reputation, Reduced Risk of Human Error, and Audit Reporting Quality. While the study does not directly measure sustainability outcomes, the identified IT-driven improvements reflect a broader conceptual alignment with sustainable development goals—particularly in terms of enhancing transparency, accountability, and operational efficiency. Future research is recommended to empirically examine the long-term sustainability impacts of IT adoption in auditing.It can be concluded that adopting integrated reporting, using technology, and actively engaging with stakeholders can increase auditors' effectiveness in promoting sustainable development.

Keywords: Information Technology Adoption, Auditing Profession, Sustainable Development.

1. Introduction

In the contemporary global landscape, the auditing profession is undergoing an unprecedented transformation driven by technological innovations, sustainability imperatives, and the growing demand for accountability and transparency. The rapid adoption of advanced information technologies, including artificial intelligence (AI), blockchain, big data analytics, and continuous auditing systems, has redefined the nature of audit practices and reshaped the expectations of stakeholders across sectors [1, 2]. At the same time, the principles of sustainable development—emphasizing economic efficiency, environmental responsibility, and social equity—have become central to organizational strategies and reporting frameworks [3, 4]. The intersection of these two domains—technology adoption in auditing and sustainability alignment—forms a critical area of scholarly inquiry and practical application.

The traditional audit approach, often characterized by periodic reviews, manual sampling, and retrospective assessments, is increasingly inadequate in addressing the complex realities of today's digital and sustainability-oriented economy. As organizations expand their operations globally and engage in more complex financial and non-financial transactions, the risks of fraud, misreporting, and information asymmetry intensify [5, 6]. The emergence of IT-based auditing methods addresses these challenges by providing tools for real-time monitoring, automated testing, and predictive analytics, thereby enhancing both audit quality and organizational resilience [7, 8]. Moreover, the sustainability agenda requires auditors to extend their scope beyond financial metrics, incorporating environmental, social, and governance (ESG) indicators into assurance processes [9, 10].

Theoretical frameworks such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT-2), and the Technology–Organization–Environment (TOE) framework have been extensively applied to explain how new technologies are adopted within the auditing profession [11-13]. For example, TAM emphasizes perceived usefulness and perceived ease of use as critical determinants of adoption, making it particularly relevant in explaining auditors' willingness to embrace tools like audit analytics and blockchain platforms [1, 14]. UTAUT-2 adds further explanatory power by considering constructs such as performance expectancy, social influence, and habitual use, factors that have proven significant in contexts such as AI-enabled auditing [12]. The TOE framework, meanwhile, highlights the organizational and environmental contexts, pointing to management support, regulatory pressures, and technological infrastructure as drivers or barriers of adoption [13, 15].

Empirical research demonstrates the transformative potential of digital audit tools in supporting sustainable development. For instance, Zhang et al. (2024) showed that the digital transformation of national audits in China not only enhanced audit efficiency but also contributed to regional environmental governance and corporate innovation [16]. Similarly, Ahmed et al. (2024) proposed a blockchain integration lifecycle model in auditing, highlighting how decentralized systems improve transparency, reduce fraud, and align audit processes with long-term sustainability outcomes [14]. In another study, Rawat (2025) emphasized the role of auditors in enhancing the credibility of sustainability disclosures, a function that has gained prominence with the proliferation of ESG reporting [9].

In the Middle Eastern and Iranian contexts, however, the adoption of IT in auditing has faced significant challenges. Barani (2019) found that while IT tools are increasingly recognized in Iranian accounting firms, their usage remains constrained by limited training and digital infrastructure [7]. Ghashghaei and Moshayekh (2019) further observed that environmental pressures and managerial support are pivotal in enabling successful technology adoption in auditing practices [13]. Delbari Ragheb and Esmailzadeh (2023) demonstrated how audit quality directly affects investor trust, underscoring the importance of technological integration to restore confidence in capital markets [17]. Salehi and Nazemi (2021) similarly argued that digital tools can enhance audit quality and reduce misstatement risks when supported by strong governance frameworks [18].

At the global level, sustainability assurance has gained momentum, but concerns remain about regulatory gaps and greenwashing. Dachevski and Ackers (2025) critically examined these challenges, pointing out that auditors are increasingly called upon to validate sustainability claims and prevent deceptive practices [10]. Du Toit (2024) also emphasized the need for robust frameworks that bridge the gap between sustainability reporting and actual performance, highlighting the role of technology in improving data reliability [19]. Dwivedi (2022) reinforced these perspectives by showing how digital and green transformations are interdependent in achieving the United Nations Sustainable Development Goals (SDGs) [3].

The integration of AI and big data analytics in auditing provides another dimension of opportunity. AI systems have been shown to reduce human error, enhance prediction capabilities, and expand the scope of audit coverage [8, 12]. By automating routine tasks and enabling auditors to focus on high-risk areas, AI not only improves efficiency but also supports sustainability by aligning resources with strategic objectives [20, 21]. Furthermore, continuous auditing models, enabled by digital infrastructures, facilitate real-time assurance and proactive risk management, representing a significant departure from the retrospective nature of traditional audits [2, 6].

From a sustainability perspective, IT adoption in auditing contributes across the economic, social, and environmental dimensions. Economically, it reduces costs, accelerates processes, and strengthens decision-making through predictive analytics [9, 15]. Socially, it enhances accountability and stakeholder trust by providing accurate, timely, and transparent information [17, 18]. Environmentally, technologies such as blockchain and remote auditing reduce the reliance on paper and physical travel, lowering the carbon footprint of audit activities [10, 19]. These impacts illustrate how auditing can function as both a control mechanism and a proactive enabler of sustainable governance.

Nevertheless, the path to IT adoption in auditing is not without barriers. Resistance to change, cybersecurity risks, and the lack of skilled human resources continue to challenge adoption processes [22, 23]. Noori Doabi et al. (2024) used fuzzy Delphi methods to highlight the complexities of blockchain adoption in accounting and auditing, emphasizing the importance of expert consensus in navigating uncertainty [22]. Sung and Hong (2023) further illustrated the role of education and knowledge transfer in fostering acceptance of IT-based systems among auditors [23]. Zare Behnamiri et al. (2023) identified blockchain as a key driver influencing the future of auditing in Iran, pointing to its potential to transform both processes and stakeholder relationships [24].

In addition, organizational culture and values are central to the success of IT adoption. Amirbeigi and Langroudi (2020) argued that auditing contributes to sustainable value creation when integrated into broader organizational strategies, aligning economic, social, and environmental objectives [20]. Farzin et al. (2018) highlighted the role of professional ethics in guiding auditors' behavior in technology-enabled contexts, ensuring that innovations are leveraged responsibly [25]. Appelbaum et al. (2021) also stressed that while technology enhances audit quality, its impact depends significantly on the ethical and professional judgment of auditors [1].

Despite significant progress, critical gaps remain in the literature. Most existing research has focused on the efficiency and technical aspects of IT adoption, while the sustainability implications are often underexplored [3, 9]. Moreover, while developed economies have generated substantial empirical evidence on digital auditing, studies in emerging markets, particularly Iran, remain scarce [7, 17]. The lack of contextualized models that account for institutional, cultural, and infrastructural dynamics limits the applicability of global frameworks to local auditing practices [13, 24].

Given these gaps, this study seeks to develop a comprehensive IT adoption model for the auditing profession that explicitly incorporates sustainability considerations, with a focus on the Iranian context. Building on theoretical frameworks such as TAM, UTAUT-2, and TOE, and integrating empirical insights from global and regional studies, the research aims to propose a model that addresses both technological and sustainability dimensions [3, 12, 14]. By identifying key drivers, barriers, and organizational pressures, the study provides both theoretical contributions and practical guidance for auditors, regulators, and policymakers seeking to align digital transformation with sustainable development goals [9, 10, 19].

Accordingly, the purpose of this study is to propose and validate an information technology adoption model for the auditing profession that supports sustainable development objectives, particularly in the context of Iran's evolving institutional and technological environment.

2. Methodology

This study adopts an applied and developmental approach, employing a mixed-methods research design to investigate the adoption of information technology in the auditing profession with a sustainable development orientation. The research was conducted over a six-month period during spring and summer of 2025 (March to August).

The study pursued two main objectives:

(1) to develop a conceptual model for the acceptance of information technology in auditing aligned with sustainable development goals; and

(2) to empirically validate this model based on field data.

In the qualitative phase, data were collected through semi-structured, face-to-face interviews with 13 selected experts. Participants were chosen using purposive sampling, based on the following criteria:

- Holding a Ph.D. or equivalent professional expertise in information systems, audit methodology, or related fields;
- Having at least 10 years of relevant professional experience in auditing or IT-based financial oversight;
- Demonstrating scientific and applied knowledge related to IT adoption in auditing systems.

Each interview lasted approximately 45 minutes, and interviews continued until theoretical saturation was achieved. The central guiding question was:

"What are the key factors influencing the adoption of information technology in the auditing profession to support sustainable development?"

The interview data were analyzed using thematic analysis, following the six-phase approach of Braun & Clarke (2006):

1. *Familiarization with the data*: Transcription and repeated reading of interviews
2. *Generating initial codes*: Identification of meaningful segments using open coding
3. *Searching for themes*: Grouping similar codes into broader conceptual themes
4. *Reviewing themes*: Refining and validating themes by checking against transcripts
5. *Defining and naming themes*: Clearly labeling the finalized themes
6. *Producing the report*: Interpreting themes and selecting representative quotes

The process was managed using MAXQDA software, enabling structured code analysis and concept development. These finalized themes formed the foundation for the development of the quantitative questionnaire.

To link the findings from the qualitative phase to the quantitative model, the research followed a structured path: interviews → thematic coding → identification of indicators → development of questionnaire items → conceptual model formation. This integration ensured that the survey instrument was grounded in practitioner insights and that the structural model reflected empirically relevant constructs.

In the quantitative phase, a structured questionnaire with 77 items was designed based on the codes extracted during the qualitative phase. The questionnaire was divided into two sections:

A 5-point Likert scale was used, ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). The target population included auditors from Tehran Stock Exchange–listed companies. As the exact population size was unknown, Cochran's formula for infinite populations was used to estimate the required sample size. Therefore, 385 respondents were required. A total of 430 questionnaires were distributed through both electronic (email/online forms) and physical (paper) formats. Of these:

- 392 responses were returned
- 385 responses were deemed valid after data screening

Content validity was established via expert evaluation. Construct validity was examined through convergent and discriminant validity. Instrument reliability was confirmed through Cronbach's alpha and Composite Reliability (CR), with all values exceeding standard thresholds.

Quantitative data were analyzed in two stages:

- Descriptive statistics using SPSS

Structural Equation Modeling (SEM) using SmartPLS to test hypotheses and validate the conceptual model

3. Findings and Results

In axial coding, which is conducted after open coding, separate categories are placed together within a meaningful framework, and the relationships between them are identified. Axial coding results in the formation of groups and categories. All similar codes are placed within their respective groups. In this process, all the generated codes are reviewed once again and compared with the texts to ensure that every detail is thoroughly examined.

Table 1. Axial Coding

Axis Code	Open Code
Big Data	1. High volume of data
	2. High speed of data processing
	3. Diversity of available data
	4. Utilization of tools or software to reduce or eliminate manual recording of reminders and task tracking
	5. Automating tasks and enhancing process efficiency
Analysis and Prediction	6. Forecasting future events through analyzing existing data
	7. Utilizing statistical, mathematical, and machine learning methods for analysis
	8. Estimating probabilities of potential occurrences
	9. Effectiveness and efficiency errors
	10. Compliance error
	11. Reporting error
Software Utility	12. New web-based financial reporting language (XBRL)
	13. Python programming language
	14. Operational utility
	15. Functional utility
	16. Quality utility
	17. Seamless utilization of technology
	18. Ease of technology use
Scientific Human Force	19. Skilled human force
	20. Informed and knowledgeable human force
	21.Human force proficient in modern technology
Data Security	22. Protecting company information
	23. Protecting reporter information
	24. Protecting user information
	25. Unauthorized access to computer data
	26. Breach of computer system security measures
	27. Deletion, destruction, disruption, or rendering unprocessable of other data from computer systems

Environmental	28. Responsibility and accountability toward the environment
	29. Continuous improvement of environmental performance
	30. Reporting environmental performance information
	31. Utilization of environmentally friendly technology
Improving efficiency	32. Attention to the rights of future generations
	33. Efficiency of human factors
	34. Efficiency of technical factors
	35. Efficiency of economic factors
	36. Reduction in data analysis time
Enhanced Analysis and Depth of Analysis	37. Reduction in report preparation time
	38. Accuracy of analysis
	39. Breakdown of data into granular units
	40. Credibility of analysis results
	41. Detection of anomalous data
	42. Detection of incorrect figures
	43. Detection of manipulated data
	44. Speed of analysis execution
	45. Speed of data processing
Improved Decision-Making	46. Speed of data entry
	47. Forecasting future financial trends based on existing data
	48. Analyzing future financial activities based on past results
	49. Selecting the best solution from available alternatives
	50. Ensuring the reliability of reporting outcomes for decision-making
Enhanced Reputation of Auditors	51. Making relevant decisions with greater confidence
	52. Auditor's credibility
	53. Increased reliance on auditor reports
	54. Enhancing the auditor's professional standing
	55. Real-time monitoring and review of data and financial activities
	56. Continuous evaluation of transactions and controls
	57. Continuous auditing
	58. Compliance testing
Reduction in Human Error Risk	59. Substantive testing of transactions
	60. Reduction of uncertainty risk in results
	61. Reduction of low-quality reporting risk
	62. Utilizing technology for data analysis
	63. Utilizing technology for report preparation
	64. Reduction in the workforce dedicated to reporting
	65. Reduction of human involvement in reporting
Audit Reporting Quality	66. Reduction of human influence on reporting
	67. Enhancing transparency
	68. Real-time analysis of financial data
	69. Reduction of discretionary accruals
	70. Reduction in cash flows
	71. Improvement in cash flow forecasting
	72. Reduction of fraud
	73. Increased relevance and timeliness of information
	74. Reduction of material misstatement risk
	75. Timely filing of audited financial statements
	76. Fewer restatements
	77. Improvement in profit forecasting

The results of axial coding are presented in the table above. As observed, 77 initial codes have been categorized into 12 overarching themes. To assess the reliability of the developed model, the kappa statistic has been employed. In this process, another individual—an expert in the field—was tasked with categorizing the codes into concepts without any prior knowledge of how the codes and concepts created by the researcher were integrated. Subsequently, the concepts presented by the researcher were compared with those articulated by this individual. Ultimately, the kappa statistic was computed based on the number of similar concepts created and the number of divergent concepts identified.

Table 2. Kappa coefficient

		Value	Standard error	Tb	Sig
Agreement Criterion	Kappa	0.809	0.117	6.914	0.000
Number of cod		12			

As observed, the calculated Kappa coefficient was 0.809, which, based on the criteria outlined in Table 2, indicates a substantial level of agreement.

The Fuzzy Delphi Technique was employed to screen and identify the final indicators. Experts' perspectives on the significance of the indicators were systematically collected. The importance of the indicators was determined based on expert opinions. We acknowledge that experts leverage their cognitive abilities to perform comparisons. However, it's important to note that the traditional process of quantifying individual perspectives cannot fully capture the nuances of human thought. In other words, the utilization of fuzzy sets aligns more closely with linguistic and sometimes ambiguous human descriptions. Therefore, it's preferable to engage in long-term forecasting and decision-making in the real world using fuzzy sets (employing fuzzy numbers). In this study, triangular fuzzy numbers were used to fuzzification expert opinions.

Table 3. Triangular Fuzzy Number

Indicator	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
C1	(6,7,8)	(7,8,9)	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)	(4,3,2)	(8,7,6)	(9,9,8)	(9,8,7)	(9,9,8)	(9,8,7)
C2	(9,9,8)	(8,7,6)	(8,7,6)	(7,6,5)	(9,8,7)	(7,6,5)	(9,8,7)	(9,8,7)	(8,7,6)	(7,6,5)	(9,9,8)	(9,9,8)
C3	(8,7,6)	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(7,6,5)	(7,6,5)	(9,8,7)	(9,9,8)	(7,6,5)	(9,8,7)	(9,8,7)
C4	(7,6,5)	(8,7,6)	(7,6,5)	(7,6,5)	(9,9,8)	(8,7,6)	(9,8,7)	(8,7,6)	(9,8,7)	(9,8,7)	(9,8,7)	(9,9,8)
C5	(9,9,8)	(9,8,7)	(9,9,8)	(7,6,5)	(8,7,6)	(9,8,7)	(3,2,1)	(9,8,7)	(9,8,7)	(8,7,6)	(9,9,8)	(9,8,7)
C6	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(1,1,1)	(9,8,7)	(9,9,8)	(8,7,6)	(9,8,7)	(9,9,8)
C7	(7,6,5)	(8,7,6)	(7,6,5)	(9,8,7)	(8,7,6)	(9,9,8)	(6,5,4)	(9,9,8)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)
C8	(7,6,5)	(9,9,8)	(8,7,6)	(9,9,8)	(9,9,8)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)	(8,7,6)	(9,9,8)	(9,9,8)
C9	(7,6,5)	(9,9,8)	(7,6,5)	(9,9,8)	(7,6,5)	(9,8,7)	(6,5,4)	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)	(9,9,8)
C10	(7,6,5)	(9,8,7)	(9,8,7)	(7,6,5)	(1,1,1)	(9,8,7)	(6,5,4)	(1,1,1)	(7,6,5)	(7,6,5)	(9,9,8)	(9,8,7)
C11	(8,7,6)	(8,7,6)	(8,7,6)	(8,7,6)	(9,9,8)	(7,6,5)	(8,7,6)	(8,7,6)	(9,8,7)	(7,6,5)	(9,8,7)	(9,8,7)
C12	(8,7,6)	(9,8,7)	(7,6,5)	(9,9,8)	(9,9,8)	(8,7,6)	(1,1,1)	(9,9,8)	(8,7,6)	(7,6,5)	(9,9,8)	(9,8,7)
C13	(7,6,5)	(9,9,8)	(7,6,5)	(9,9,8)	(8,7,6)	(9,9,8)	(3,2,1)	(7,6,5)	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)
C14	(9,9,8)	(9,9,8)	(8,7,6)	(7,6,5)	(8,7,6)	(9,9,8)	(8,7,6)	(9,9,8)	(7,6,5)	(9,8,7)	(9,8,7)	(9,9,8)
C15	(9,9,8)	(8,7,6)	(7,6,5)	(9,9,8)	(8,7,6)	(9,8,7)	(8,7,6)	(9,9,8)	(9,8,7)	(9,9,8)	(9,8,7)	(9,9,8)
C16	(7,6,5)	(8,7,6)	(7,6,5)	(9,8,7)	(9,8,7)	(9,8,7)	(6,5,4)	(9,8,7)	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)
C17	(9,9,8)	(9,9,8)	(8,7,6)	(8,7,6)	(7,6,5)	(7,6,5)	(3,2,1)	(9,9,8)	(8,7,6)	(9,8,7)	(9,8,7)	(9,9,8)

C18	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)	(8,7,6)	(9,8,7)	(5,4,3)	(9,8,7)	(8,7,6)	(9,8,7)	(9,8,7)	(9,8,7)
C19	(9,9,8)	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)	(8,7,4)	(3,2,1)	(8,7,6)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)
C20	(7,6,5)	(9,8,7)	(9,8,7)	(8,7,6)	(9,8,7)	(7,6,5)	(7,6,5)	(9,9,8)	(7,6,5)	(8,7,6)	(9,9,8)	(9,9,8)
C21	(9,8,7)	(9,8,7)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)	(9,9,8)	(9,9,8)	(9,8,7)	(8,7,6)	(9,8,7)	9,9,8)
C22	(9,9,8)	(9,8,7)	(8,7,6)	(9,8,7)	(9,8,7)	(9,8,7)	(3,2,1)	(9,9,8)	(9,9,8)	(9,8,7)	(9,8,7)	(9,8,7)
C23	(8,7,6)	(9,9,8)	(9,8,7)	(9,9,8)	(9,9,8)	(9,9,8)	(1,1,1)	(9,8,7)	(9,9,8)	(8,7,6)	(9,9,8)	(9,8,7)
C24	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)	(8,7,6)	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)	(9,8,7)	(9,8,7)	(9,8,7)
C25	(9,8,7)	(8,7,6)	(8,7,6)	(7,6,5)	(9,8,7)	(7,6,5)	(9,8,7)	(9,9,8)	(9,8,7)	(8,7,6)	(9,8,7)	(9,8,7)
C26	(9,8,7)	(9,9,8)	(7,6,5)	(9,9,8)	(7,6,5)	(9,9,8)	(5,4,3)	(8,7,6)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)
C27	(9,8,7)	(8,7,6)	(9,8,7)	(9,8,7)	(9,9,8)	(9,8,7)	(9,9,8)	(8,7,6)	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)
C28	(9,8,7)	(9,8,7)	(7,6,5)	(7,6,5)	(8,7,6)	(9,8,7)	(6,5,4)	(9,8,7)	(7,6,5)	(7,6,5)	(9,9,8)	(9,9,8)
C29	(9,9,8)	(9,9,8)	(8,7,6)	(9,9,8)	(8,7,6)	(7,6,5)	(7,6,5)	(8,7,6)	(7,6,5)	(7,6,5)	(9,9,8)	(9,9,8)
C30	(7,6,5)	(9,8,7)	(9,9,8)	(7,6,5)	(9,8,7)	(9,8,7)	(5,4,3)	(9,8,7)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)
C31	(8,7,6)	(9,9,8)	(9,8,7)	(7,6,5)	(8,7,6)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)	(8,7,6)	(9,9,8)	(9,8,7)
C32	(9,8,7)	(8,7,6)	(7,6,5)	(8,7,6)	(9,9,8)	(8,7,6)	(4,3,2)	(8,7,6)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)
C33	(9,9,8)	(9,8,7)	(9,9,8)	(7,6,5)	(8,7,6)	(9,8,7)	(3,2,1)	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(9,9,8)
C34	(7,6,5)	(9,9, 8)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)	(1,1,1)	(9,8,7)	(7,6,5)	(9,8,7)	(9,9,8)	(9,8,7)
C35	(7,6,5)	(8,7,6)	(9,9,8)	(7,6,5)	(8,7,6)	(7,6,5)	(9,9,8)	(7,6,5)	(8,7,6)	(9,8,7)	(9,8,7)	(9,9,8)
C36	(9,9,8)	(9,9,8)	(7,6,5)	(7,6,5)	(8,7,6)	(9,8,7)	(9,8,7)	(8,7,6)	(8,7,6)	(8,7,6)	(9,9,8)	(9,9,8)
C37	(9,8,7)	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)	(9,9,8)	(3,2,1)	(7,6,5)	(8,7,6)	(9,9,8)	(9,9,8)	(9,8,7)
C38	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)	(9,9,8)	(7,6,5)	(4,3,2)	(9,9,8)	(8,7,6)	(9,9,8)	(9,8,7)	(9,8,7)
C39	(8,7,6)	(9,9,8)	(7,6,5)	(9,8,7)	(8,7,6)	(9,9,8)	(8,7,6)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)	(9,8,7)
C40	(8,7,6)	(9,8,7)	(9,8,7)	(7,6,5)	(7,6,5)	(9,9,8)	(9,9,8)	(9,8,7)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)
C41	(7,6,5)	(8,7,6)	(7,6,5)	(7,6,5)	(7,6,5)	(8,7,6)	(7,6,5)	(9,8,7)	(8,7,6)	(1,1,1)	(9,8,7)	(9,8,7)
C42	(9,8,7)	(9,8,7)	(8,7,6)	(9,8,7)	(7,6,5)	(8,7,6)	(8,7,6)	(9,8,7)	(7,6,5)	(8,7,6)	(9,9,8)	(9,9,8)
C43	(9,9,8)	(9,9,8)	(8,7,6)	(9,9,8)	(8,7,6)	(7,6,5)	(5,4,3)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)	(9,9,8)
C44	(8,7,6)	(8,7,6)	(9,9,8)	(7,6,5)	(9,8,7)	(8,7,6)	(4,3,2)	(9,9,8)	(9,8,7)	(9,8,7)	(9,8,7)	(9,8,7)
C45	(9,9,8)	(9,8,7)	(7,6,5)	(7,6,5)	(9,9,8)	(8,7,6)	(7,6,5)	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(9,9,8)
C46	(8,7,6)	(8,7,6)	(9,8,7)	(9,8,7)	(7,6,5)	(9,8,7)	(9,8,7)	(8,7,6)	(8,7,6)	(8,7,6)	(9,8,7)	(9,9,8)
C47	(9,8,7)	(9,8,7)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)	(3,2,1)	(9,9,8)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)
C48	(9,9,8)	(9,9,8)	(8,7,6)	(8,7,6)	(8,7,6)	(7,6,5)	(9,9,8)	(7,6,5)	(8,7,6)	(9,8,7)	(9,8,7)	(9,8,7)
C49	(9,8,7)	(9,8,7)	(7,6,5)	(8,7,6)	(9,8,7)	(9,8,7)	(8,7,6)	(7,6,5)	(8,7,6)	(7,6,5)	(9,8,7)	(9,8,7)
C50	(9,8,7)	(9,9,8)	(9,9,8)	(9,9,8)	(8,7,6)	(9,8,7)	(5,4,3)	(9,9,8)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)
C51	(8,7,6)	(9,8,7)	(9,8,7)	(9,8,7)	(9,8,7)	(9,8,7)	(8,7,6)	(9,8,7)	(9,9,8)	(9,9,8)	(9,8,7)	(9,8,7)
C52	(7,6,5)	(9,8,7)	(8,7,6)	(1,1,1)	(8,7,6)	(1,1,1)	(8,7,6)	(1,1,1)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)
C53	(9,8,7)	(9,8,7)	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(6,5,4)	(7,6,5)	(8,7,6)	(8,7,6)	(9,8,7)	(9,9,8)
C54	(9,8,7)	(9,9,8)	(9,9,8)	(9,9,8)	(8,7,6)	(9,9,8)	(6,5,4)	(7,6,5)	(7,6,5)	(9,8,7)	(9,9,8)	(9,8,7)
C55	(8,7,6)	(9,8,7)	(8,7,6)	(8,7,6)	(7,6,5)	(9,8,7)	(8,7,6)	(7,6,5)	(9,8,7)	(7,6,5)	(9,8,7)	(9,9,8)
C56	(7,6,5)	(9,9,8)	(9,9,8)	(7,6,5)	(8,7,6)	(9,9,8)	(7,6,5)	(7,6,5)	(9,8,7)	(9,9,8)	(9,8,7)	(9,8,7)
C57	(9,9,8)	(9,8,7)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)	(1,1,1)	(9,9,8)	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)
C58	(7,6,5)	(9,8,7)	(9,8,7)	(8,7,6)	(9,9,8)	(9,9,8)	(6,5,4)	(9,9,8)	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)
C59	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(7,6,5)	(7,6,5)	(8,7,6)	(9,8,7)	(7,6,5)	(9,8,7)	(9,8,7)	(9,9,8)
C60	(7,6,5)	(9,8,7)	(9,8,7)	(8,7,6)	(9,9,8)	(9,9,8)	(6,5,4)	(9,9,8)	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)
C61	(9,9,8)	(9,9,8)	(7,6,5)	(9,8,7)	(7,6,5)	(7,6,5)	(8,7,6)	(9,8,7)	(7,6,5)	(9,8,7)	(9,8,7)	(9,9,8)

C62	(8,7,6)	(9,9,8)	(8,7,6)	(9,9,8)	(9,9,8)	(7,6,5)	(9,9,8)	(8,7,6)	(7,6,5)	(8,7,6)	(9,9,8)	(9,9,8)
C63	(7,6,5)	(9,9,8)	(9,8,7)	(7,6,5)	(8,7,6)	(7,6,5)	(3,2,1)	(9,9,8)	(9,9,8)	(7,6,5)	(9,9,8)	(9,9,8)
C64	(7,6,5)	(9,8,7)	(9,8,7)	(7,6,5)	(9,8,7)	(8,7,6)	(9,8,7)	(9,9,8)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)
C65	(9,9,8)	(8,7,6)	(8,7,6)	(7,6,5)	(8,7,6)	(8,7,6)	(6,5,4)	(9,9,8)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)
C66	(9,8,7)	(8,7,6)	(8,7,6)	(9,9,8)	(9,8,7)	(9,9,8)	(6,5,4)	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)	(9,9,8)
C67	(9,8,7)	(8,7,6)	(7,6,5)	(7,6,5)	(8,7,6)	(9,8,7)	(9,9,8)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)	(9,8,7)
C68	(7,6,5)	(8,7,6)	(9,8,7)	(7,6,5)	(8,7,6)	(9,9,8)	(3,2,1)	(7,6,5)	(9,8,7)	(9,9,8)	(9,9,8)	(9,8,7)
C69	(7,6,5)	(9,8,7)	(8,7,6)	(1,1,1)	(8,7,6)	(1,1,1)	(8,7,6)	(1,1,1)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)
C70	(8,7,6)	(9,8,7)	(8,7,6)	(,9,9,8)	(7,6,5)	(7,6,5)	(9,9,8)	(8,7,6)	(7,6,5)	(9,9,8)	(9,9,8)	(9,9,8)
C71	(9,8,7,)	(8,7,6)	(7,6,5)	(8,7,6)	(7,6,5)	(9,8,7)	(9,8,7)	(9,8,7)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)
C72	(8,7,6)	(9,8,7)	(9,9,8)	(9,8,7)	(8,7,6)	(7,6,5)	(4,3,2)	(9,9,8)	(9,9,8)	(7,6,5)	(9,9,8)	(9,8,7)
C73	(8,7,6)	(9,8,7)	(7,6,5)	(9,9,8)	(7,6,5)	(9,9,8)	(9,9,8)	(8,7,6)	(7,6,5)	(7,6,5)	(9,8,7)	(9,8,7)
C74	(1,1,1)	(9,9,8)	(7,6,5)	(8,7,6)	(1,1,1)	(1,1,1)	(8,7,6)	(1,1,1)	(7,6,5)	(8,7,6)	(9,9,8)	(9,8,7)
C75	(9,8,7)	(9,8,7)	(8,7,6)	(9,8,7)	(8,7,6)	(8,7,6)	(4,3,2)	(9,9,8)	(9,8,7)	(9,9,8)	(9,8,7)	(9,8,7)
C76	(9,8,7)	(8,7,6)	(7,6,5)	(9,8,7)	(9,9,8)	(9,9,8)	(9,9,8)	(8,7,6)	(9,9,8)	(9,9,8)	(9,9,8)	(9,9,8)
C77	(8,7,6)	(8,7,6)	(9,9,8)	(9,8,7)	(8,7,6)	(7,6,5)	(1,1,1)	(7,6,5)	(9,9,8)	(9,9,8)	(9,8,7)	(9,9,8)

The fuzzy mean and defuzzified values for the indicators are presented in Table 4. A defuzzified value greater than 0.7 is considered acceptable, and any indicator with a score less than 0.7 is rejected.

Table 4. Fuzzy Averages and Fuzzy Screening of Indicators (Round One)

R1	L	M	U	mean	Crisp	Result
C1	6.58	7.58	8.25	(8.25,7.58,6.58)	7.47	Acceptance
C2	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance
C3	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance
C4	6.42	7.42	8.25	(8.25,7.42,6.42)	7.36	Acceptance
C5	6.42	7.42	8.17	(8.17,7.42,6.42)	7.34	Acceptance
C6	6.50	7.42	7.92	(7.92,7.42,6.5)	7.28	Acceptance
C7	6.25	7.25	8.00	(8,7.25,6.25)	7.17	Acceptance
C8	6.92	7.92	8.42	(8.42,7.92,6.92)	7.75	Acceptance
C9	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C10	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C11	6.25	7.25	8.17	(8.17,7.25,6.25)	7.22	Acceptance
C12	6.25	7.17	7.75	(7.75,7.17,6.25)	7.06	Acceptance
C13	6.25	7.25	7.75	(7.75,7.25,6.25)	7.08	Acceptance
C14	6.83	7.83	8.42	(8.42,7.83,6.83)	7.69	Acceptance
C15	7.00	8.00	8.58	(8.58,8,7)	7.86	Acceptance
C16	6.42	7.42	8.17	(8.17,7.42,6.42)	7.34	Acceptance
C17	6.25	7.25	7.92	(7.92,7.25,6.25)	7.14	Acceptance
C18	6.50	7.50	8.42	(8.42,7.5,6.5)	7.47	Acceptance
C19	6.25	7.25	7.92	(7.92,7.25,6.25)	7.14	Acceptance
C20	6.42	7.42	8.17	(8.17,7.42,6.42)	7.34	Acceptance
C21	7.00	8.00	8.67	(8.67,8,7)	7.89	Acceptance
C22	6.67	7.67	8.42	(8.42,7.67,6.67)	7.59	Acceptance
C23	6.83	7.75	8.17	(8.17,7.75,6.83)	7.58	Acceptance

C24	6.92	7.92	8.67	(8.67,7.92,6.92)	7.84	Acceptance
C25	6.50	7.50	8.42	(8.42,7.5,6.5)	7.47	Acceptance
C26	6.75	7.75	8.25	(8.25,7.75,6.75)	7.58	Acceptance
C27	7.00	8.00	8.67	(8.67,8,7)	7.89	Acceptance
C28	6.17	7.17	8.00	(8,7.17,6.17)	7.11	Acceptance
C29	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C30	6.08	7.08	8.00	(8,7.08,6.08)	7.05	Acceptance
C31	6.58	7.58	8.33	(8.33,7.58,6.58)	7.50	Acceptance
C32	6.42	7.42	8.08	(8.08,7.42,6.42)	7.31	Acceptance
C33	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C34	6.58	7.50	8.00	(8,7.5,6.58)	7.36	Acceptance
C35	6.33	7.33	8.08	(8.08,7.33,6.33)	7.25	Acceptance
C36	6.67	7.67	8.33	(8.33,7.67,6.67)	7.56	Acceptance
C37	6.50	7.50	8.17	(8.17,7.5,6.5)	7.39	Acceptance
C38	6.42	7.42	8.08	(8.08,7.42,6.42)	7.31	Acceptance
C39	6.58	7.58	8.33	(8.33,7.58,6.58)	7.50	Acceptance
C40	6.42	7.42	8.25	(8.25,7.42,6.42)	7.36	Acceptance
C41	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C42	6.50	7.50	8.33	(8.33,7.5,6.5)	7.44	Acceptance
C43	6.92	7.92	8.33	(8.33,7.92,6.92)	7.72	Acceptance
C44	6.33	7.33	8.17	(8.17,7.33,6.33)	7.28	Acceptance
C45	6.67	7.67	8.25	(8.25,7.67,6.67)	7.53	Acceptance
C46	6.50	7.50	8.42	(8.42,7.5,6.5)	7.47	Acceptance
C47	6.67	7.67	8.25	(8.25,7.67,6.67)	7.53	Acceptance
C48	6.58	7.58	8.33	(8.33,7.58,6.58)	7.50	Acceptance
C49	6.25	7.25	8.25	(8.25,7.25,6.25)	7.25	Acceptance
C50	6.75	7.75	8.33	(8.33,7.75,6.75)	7.61	Acceptance
C51	7.00	8.00	8.83	(8.83,8,7)	7.94	Acceptance
C52	6.50	7.50	8.08	(8.08,7.5,6.5)	7.36	Acceptance
C53	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance
C54	6.75	7.75	8.33	(8.33,7.75,6.75)	7.61	Acceptance
C55	6.25	7.25	8.17	(8.17,7.25,6.25)	7.22	Acceptance
C56	6.58	7.58	8.25	(8.25,7.58,6.58)	7.47	Acceptance
C57	6.92	7.83	8.25	(8.25,7.83,6.92)	7.67	Acceptance
C58	6.83	7.83	8.33	(8.33,7.83,6.83)	7.66	Acceptance
C59	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance
C60	6.83	7.83	8.33	(8.33,7.83,6.83)	7.66	Acceptance
C61	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance
C62	6.83	7.83	8.33	(8.33,7.83,6.83)	7.66	Acceptance
C63	6.17	7.17	7.75	(7.75,7.17,6.17)	7.03	Acceptance
C64	6.50	7.50	8.33	(8.33,7.5,6.5)	7.44	Acceptance
C65	6.25	7.25	8.00	(8,7.25,6.25)	7.17	Acceptance
C66	6.83	7.83	8.50	(8.5,7.83,6.83)	7.72	Acceptance
C67	6.33	7.33	8.17	(8.17,7.33,6.33)	7.28	Acceptance
C68	6.17	7.17	7.83	(7.83,7.17,6.17)	7.06	Acceptance
C69	6.17	7.17	8.17	(8.17,7.17,6.17)	7.14	Acceptance

C70	6.67	7.67	8.25	(8.25,7.67,6.67)	7.53	Acceptance
C71	6.33	7.33	8.25	(8.25,7.33,6.33)	7.30	Acceptance
C72	6.42	7.42	8.08	(8.08,7.42,6.42)	7.31	Acceptance
C73	6.42	7.42	8.17	(8.17,7.42,6.42)	7.34	Acceptance
C74	6.92	7.83	8.25	(8.25,7.83,6.92)	7.67	Acceptance
C75	6.50	7.50	8.33	(8.33,7.5,6.5)	7.44	Acceptance
C76	7.25	8.25	8.67	(8.67,8.25,7.25)	8.06	Acceptance
C77	6.25	7.17	7.75	(7.75,7.17,6.25)	7.06	Acceptance

All items scored higher than 0.7 and remained in the Delphi process, moving to the second round for agreement analysis.

Fuzzy Delphi analysis continued for the remaining indicators in the second round. The results of defuzzification the elements in the second round are reported in Table 5.

Table 5. Fuzzy Mean and Fuzzy Screening of Indicators (Round Two) and Difference Between Definite Values of Round One and Round Two

R2	L	M	U	mean	Crisp	Result	Difference	Result
C1	7.08	8.08	8.75	(8.75,8.08,7.08)	7.57	Acceptance	0.1	Agreement
C2	6.42	7.42	8.33	(8.33,7.42,6.42)	7.39	Acceptance	-0.03	Agreement
C3	6.67	7.67	8.58	(8.58,7.67,6.67)	7.54	Acceptance	0.12	Agreement
C4	6.83	7.83	8.50	(8.5,7.83,6.83)	7.32	Acceptance	-0.04	Agreement
C5	7.25	8.25	8.75	(8.75,8.25,7.25)	7.38	Acceptance	0.04	Agreement
C6	7.08	8.08	8.75	(8.75,8.08,7.08)	7.27	Acceptance	-0.01	Agreement
C7	6.75	7.75	8.42	(8.42,7.75,6.75)	7.24	Acceptance	0.07	Agreement
C8	6.75	7.75	8.50	(8.5,7.75,6.75)	7.67	Acceptance	-0.08	Agreement
C9	6.83	7.83	8.67	(8.67,7.83,6.83)	7.28	Acceptance	-0.08	Agreement
C10	7.08	8.08	8.75	(8.75,8.08,7.08)	7.27	Acceptance	-0.09	Agreement
C11	6.83	7.83	8.58	(8.58,7.83,6.83)	7.15	Acceptance	-0.07	Agreement
C12	7.25	8.25	8.83	(8.83,8.25,7.25)	7.11	Acceptance	0.05	Agreement
C13	6.58	7.58	8.50	(8.5,7.58,6.58)	7.55	Acceptance	0.47	Agreement
C14	6.83	7.83	8.50	(8.5,7.83,6.83)	7.84	Acceptance	0.15	Agreement
C15	7.00	8.00	8.58	(8.58,8,7)	7.36	Acceptance	-0.5	Agreement
C16	6.42	7.42	8.17	(8.17,7.42,6.42)	7.34	Acceptance	0	Agreement
C17	6.25	7.25	7.92	(7.92,7.25,6.25)	7.44	Acceptance	0.3	Agreement
C18	6.50	7.50	8.42	(8.42,7.5,6.5)	7.27	Acceptance	-0.2	Agreement
C19	6.25	7.25	7.92	(7.92,7.25,6.25)	7.14	Acceptance	0	Agreement
C20	6.42	7.42	8.17	(8.17,7.42,6.42)	7.84	Acceptance	0.5	Agreement
C21	7.00	8.00	8.67	(8.67,8,7)	7.59	Acceptance	-0.3	Agreement
C22	6.67	7.67	8.42	(8.42,7.67,6.67)	7.59	Acceptance	0	Agreement
C23	6.83	7.75	8.17	(8.17,7.75,6.83)	7.88	Acceptance	0.3	Agreement
C24	6.92	7.92	8.67	(8.67,7.92,6.92)	7.54	Acceptance	-0.3	Agreement
C25	6.50	7.50	8.25	(8.25,7.5,6.5)	7.62	Acceptance	0.15	Agreement
C26	7.08	8.08	8.75	(8.75,8.08,7.08)	7.97	Acceptance	0.39	Agreement
C27	7.08	8.08	8.75	(8.75,8.08,7.08)	7.17	Acceptance	-0.72	Agreement
C28	7.42	8.42	8.83	(8.83,8.42,7.42)	7.22	Acceptance	0.11	Agreement
C29	7.42	8.42	8.83	(8.83,8.42,7.42)	7.22	Acceptance	-0.14	Agreement

C30	7.00	8.00	8.67	(8.67,8,7)	7.49	Acceptance	0.44	Agreement
C31	7.08	8.08	8.75	(8.75,8.08,7.08)	7.37	Acceptance	-0.13	Agreement
C32	7.33	8.33	8.83	(8.83,8.33,7.33)	7.36	Acceptance	0.05	Agreement
C33	6.92	7.92	8.58	(8.58,7.92,6.92)	7.41	Acceptance	0.05	Agreement
C34	7.08	8.08	8.75	(8.75,8.08,7.08)	7.27	Acceptance	-0.09	Agreement
C35	6.67	7.67	8.58	(8.58,7.67,6.67)	7.64	Acceptance	0.39	Agreement
C36	7.17	8.17	8.75	(8.75,8.17,7.17)	7.43	Acceptance	-0.13	Agreement
C37	7.25	8.25	8.75	(8.75,8.25,7.25)	7.38	Acceptance	-0.01	Agreement
C38	6.83	7.83	8.50	(8.5,7.83,6.83)	7.42	Acceptance	0.11	Agreement
C39	6.58	7.58	8.33	(8.33,7.58,6.58)	7.5	Acceptance	0	Agreement
C40	6.42	7.42	8.25	(8.25,7.42,6.42)	7.36	Acceptance	0	Agreement
C41	6.08	7.08	7.92	(7.92,7.08,6.08)	7.83	Acceptance	0.47	Agreement
C42	6.50	7.50	8.33	(8.33,7.5,6.5)	7.44	Acceptance	0	Agreement
C43	6.92	7.92	8.33	(8.33,7.92,6.92)	7.72	Acceptance	0	Agreement
C44	6.33	7.33	8.17	(8.17,7.33,6.33)	7.28	Acceptance	0	Agreement
C45	6.67	7.67	8.25	(8.25,7.67,6.67)	7.53	Acceptance	0	Agreement
C46	6.50	7.50	8.42	(8.42,7.5,6.5)	7.47	Acceptance	0	Agreement
C47	6.67	7.67	8.25	(8.25,7.67,6.67)	7.33	Acceptance	-0.2	Agreement
C48	6.58	7.58	8.33	(8.33,7.58,6.58)	7.5	Acceptance	0	Agreement
C49	6.25	7.25	8.25	(8.25,7.25,6.25)	7.85	Acceptance	0.6	Agreement
C50	6.75	7.75	8.33	(8.33,7.75,6.75)	7.61	Acceptance	0	Agreement
C51	7.00	8.00	8.83	(8.83,8,7)	7.64	Acceptance	-0.3	Agreement
C52	6.58	7.58	8.17	(8.17,7.58,6.58)	7.24	Acceptance	-0.12	Agreement
C53	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance	0	Agreement
C54	6.75	7.75	8.33	(8.33,7.75,6.75)	7.61	Acceptance	0	Agreement
C55	6.25	7.25	8.17	(8.17,7.25,6.25)	7.72	Acceptance	0.5	Agreement
C56	6.58	7.58	8.25	(8.25,7.58,6.58)	7.47	Acceptance	0	Agreement
C57	6.92	7.83	8.25	(8.25,7.83,6.92)	7.67	Acceptance	0	Agreement
C58	6.83	7.83	8.33	(8.33,7.83,6.83)	7.06	Acceptance	-0.6	Agreement
C59	6.50	7.50	8.25	(8.25,7.5,6.5)	7.42	Acceptance	0	Agreement
C60	7.08	8.08	8.75	(8.75,8.08,7.08)	7.97	Acceptance	0.31	Agreement
C61	7.42	8.42	8.83	(8.83,8.42,7.42)	8.22	Acceptance	0.8	Agreement
C62	7.42	8.42	8.83	(8.83,8.42,7.42)	8.22	Acceptance	0.56	Agreement
C63	7.00	8.00	8.67	(8.67,8,7)	7.89	Acceptance	0.86	Agreement
C64	7.08	8.08	8.75	(8.75,8.08,7.08)	7.97	Acceptance	0.53	Agreement
C65	7.33	8.33	8.83	(8.83,8.33,7.33)	8.16	Acceptance	0.99	Agreement
C66	6.92	7.92	8.58	(8.58,7.92,6.92)	7.81	Acceptance	0.09	Agreement
C67	7.08	8.08	8.75	(8.75,8.08,7.08)	7.97	Acceptance	0.69	Agreement
C68	6.67	7.67	8.58	(8.58,7.67,6.67)	7.64	Acceptance	0.58	Agreement
C69	7.17	8.17	8.75	(8.75,8.17,7.17)	8.03	Acceptance	2.53	Agreement
C70	7.25	8.25	8.75	(8.75,8.25,7.25)	8.08	Acceptance	0.55	Agreement
C71	6.83	7.83	8.50	(8.5,7.83,6.83)	7.72	Acceptance	0.42	Agreement
C72	6.58	7.58	8.33	(8.33,7.58,6.58)	7.50	Acceptance	0.19	Agreement
C73	6.42	7.42	8.25	(8.25,7.42,6.42)	7.36	Acceptance	0.02	Agreement
C74	6.08	7.08	7.92	(7.92,7.08,6.08)	7.03	Acceptance	-0.64	Agreement
C75	6.50	7.50	8.33	(8.33,7.5,6.5)	7.44	Acceptance	0	Agreement

C76	6.92	7.92	8.33	(8.33,7.92,6.92)	7.72	Acceptance	-0.34	Agreement
C77	6.33	7.33	8.17	(8.17,7.33,6.33)	7.28	Acceptance	0.22	Agreement

No indicators were eliminated during the second round. This indicates the conclusion of the Delphi rounds. In general, one approach to ending the Delphi process is to compare the average scores of the questions between the first and second rounds. If the difference between the two stages is smaller than the very low threshold (0.8), the survey process is stopped.

The most important objective of Confirmatory Factor Analysis (CFA) is to evaluate the fit of a predefined factor model to a set of observed data. In other words, CFA aims to determine whether the number of factors and the loadings of variables measured on these factors match the theoretical framework and proposed model. Essentially, this type of factor analysis assesses the degree of alignment between the theoretical construct and the empirical construct of the study. In this method, variables and their corresponding indicators are initially selected based on an underlying theory. Then, factor analysis is employed to determine whether these variables and indicators load onto the predicted factors as expected, or whether their composition has changed and they load onto different factors.

In this type of factor analysis, the fundamental assumption of the researcher is that each factor is associated with a specific subset of indicators. The minimum necessary condition for conducting Confirmatory Factor Analysis (CFA) is that the researcher estimates the number of factors within the model beforehand. However, it is common for the researcher to incorporate their expectations into the hypotheses, particularly regarding which factors will load onto which variables. For instance, the researcher attempts to determine whether the variables used to construct and represent a latent variable truly belong to the same construct. Thus, using this method, it is possible to exclude inconsistent items within a scale that load very highly or very poorly on multiple factors. This is because such variables cannot be attributed to a specific factor

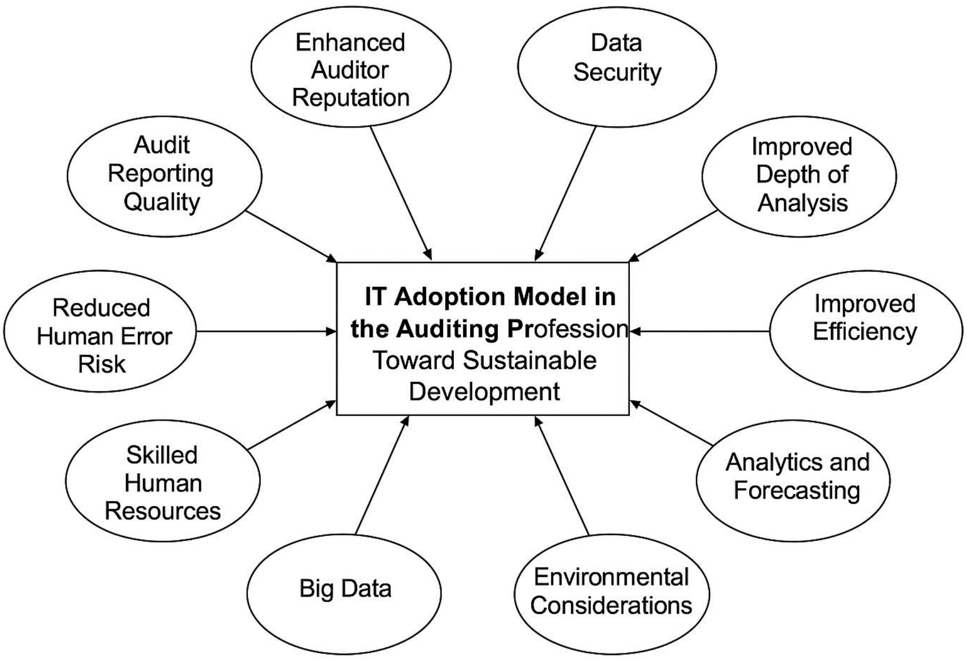

Figure 1. The Model of Information Technology Adoption in the Auditing Profession for Shaping Sustainable Development

Figure 2. Path analysis results from the structural equation model examining the impact of IT adoption on auditing-related outcomes supporting sustainable development

The structural equation model (SEM) illustrates the relationships between the core construct—IT Adoption in the Auditing Profession Toward Sustainable Development—and twelve associated outcome variables. Each path is quantified through its standardized path coefficient (β) and t-value, which indicate the strength and statistical significance of the relationships.

Table 6. Model Results Summary

Outcome Variable	Path Coefficient (β)	t-value	Interpretation
Improved Depth of Analysis	0.857	43.461	Very strong and significant impact
Improved Decision-Making	0.856	30.090	Strong and significant relationship
Reduced Human Error Risk	0.823	18.481	Strong relationship; statistically significant
Enhanced Decision-Making	0.825	38.441	Strong relationship with high confidence
Enhanced Auditor Reputation	0.821	34.941	Significant positive influence
Data Security	0.773	22.554	Moderate to strong relationship; statistically significant
Big Data	0.765	22.554	Moderate influence; statistically valid
Analytics and Forecasting	0.817	31.607	Strong influence on decision-support systems
Software Usefulness	0.840	31.540	Highly significant effect
Environmental Considerations	0.759	30.551	Positive and statistically relevant
Improved Efficiency	0.617	46.659	Lower path coefficient, but very high t-value suggests a stable relationship
Data Purity (possible typo in diagram)	0.773	22.54	Significant influence—may need clarification in label

The results suggest that IT adoption significantly contributes to multiple dimensions of audit quality and sustainability, particularly in areas such as analytical depth, decision support, risk reduction, and efficiency. All path coefficients exceed 0.6, and all t-values surpass the 1.96 threshold, indicating that the relationships are statistically significant at the 95% confidence level or higher.

4. Discussion and Conclusion

The findings of this study offer valuable insights into the dynamics of information technology (IT) adoption in the auditing profession with a focus on sustainability. The structural equation modeling results validated twelve key dimensions influencing IT adoption, including big data, predictive analytics, software utility, skilled human resources, data security, environmental considerations, improved efficiency, analytical depth, decision-making quality, auditor reputation, reduced human error, and audit reporting quality. Together, these dimensions provide a comprehensive framework that not only enhances audit effectiveness but also contributes to sustainable development objectives by embedding accountability, transparency, and long-term value creation.

A central result of the study is the significant role of perceived usefulness and organizational support in shaping IT adoption among auditors. This aligns with the Technology Acceptance Model (TAM), which emphasizes perceived usefulness as a determinant of user intention to adopt digital tools [1, 11]. In the context of auditing, auditors who perceive IT as enhancing efficiency, accuracy, and transparency are more inclined to integrate such technologies into practice. Previous studies corroborate these findings, demonstrating that digital audit tools increase audit quality and reduce misstatements when organizational support and training are provided [7, 18]. This confirms that technological innovation alone is insufficient; the institutional environment and managerial commitment remain decisive for successful adoption.

The results also revealed that sustainability-oriented pressures—such as the demand for transparent ESG reporting and stakeholder accountability—emerged as strong drivers of IT adoption. This finding supports the growing body of literature emphasizing the role of external sustainability pressures in motivating digital transformation [3, 9, 19]. For example, Rawat (2025) argued that auditors enhance the credibility of sustainability disclosures when equipped with IT-based tools that ensure accurate and timely data validation. Similarly, Du Toit (2024) highlighted that integrating IT in sustainability reporting bridges gaps between disclosure frameworks and actual performance. Our findings confirm these assertions by empirically demonstrating that IT adoption is positively influenced by sustainability imperatives, making auditors key players in advancing sustainable governance.

Another significant contribution of this study is its evidence that skilled human resources are vital for IT adoption in auditing. While advanced technologies provide the infrastructure for transformation, their effective application depends on auditors' knowledge and expertise. This finding supports earlier observations that professional competence mediates the link between technology availability and adoption success [20, 25]. Amirbeigi and Langroudi (2020) stressed that auditors must be trained not only in technical proficiency but also in sustainability-oriented value creation. Farzin et al. (2018) further emphasized the ethical dimensions of professional practice, underscoring that auditors' decisions are guided not just by technical expertise but by professional ethics. By highlighting human resources as a central factor, our results confirm that digital transformation is as much a people-centered process as it is a technical shift.

The role of data security and trust also emerged strongly in this study, reflecting auditors' concerns about cybersecurity, privacy, and system reliability. These findings echo Al-Okaily's (2022) results, which demonstrated that the adoption of audit software in Jordan was significantly influenced by auditors' perceptions of data integrity and system security. Similar conclusions were drawn by Ahmed et al. (2024), who showed that blockchain integration in auditing provides immutable records, reducing fraud risks and enhancing trust in financial systems. Our results thus validate the growing emphasis on data security as a prerequisite for IT adoption, particularly in contexts where stakeholders demand transparency and accountability [14, 22].

In terms of continuous auditing and predictive analytics, the study identified their strong influence on audit efficiency and decision-making. This finding aligns with Vasarhelyi and Romero (2023), who described continuous auditing as a cornerstone of modern assurance systems, enabling real-time monitoring and proactive risk detection. Likewise, Tarasi et al. (2019) demonstrated the power of predictive analytics through neural networks in detecting fraudulent reporting, highlighting the potential of AI and machine learning in enhancing audit accuracy. Our results provide empirical evidence that continuous auditing and predictive analytics are not only technically feasible but also strongly associated with improved decision-making quality and reduced human error in practice [8, 12].

The inclusion of environmental considerations as a validated construct demonstrates the dual role of IT in auditing: enhancing technical efficiency and supporting sustainability. Previous research emphasized that digital auditing reduces paper usage, travel, and manual processes, thereby lowering the carbon footprint [10, 19]. Our findings confirm this indirect but significant contribution of IT adoption to sustainability by embedding environmental responsibility within audit practices. The findings are consistent with Zhang et al. (2024), who found that national audit digitalization in China contributed to both environmental governance and corporate innovation. This convergence suggests that IT adoption in auditing is not a narrow technical matter but a broader strategic initiative with environmental and social benefits.

Another key insight relates to audit reporting quality and stakeholder trust, which were both improved through IT adoption. The results indicate that IT tools enhance transparency, timeliness, and accuracy of reports, thereby reducing discretionary accruals and material misstatements. These findings corroborate the work of Delbari Ragheb and Esmailzadeh (2023), who highlighted the role of audit quality in shaping investor trust, and Salehi and Nazemi (2021), who demonstrated that digital tools reduce errors and strengthen financial reporting integrity. By integrating technology, auditors can provide more credible information that directly supports capital market stability and investor confidence [17, 18].

The study also found that organizational and cultural factors act as both enablers and barriers. Resistance to change, lack of awareness, and insufficient managerial commitment were reported as obstacles to adoption. These findings are consistent with those of Zare Behnamiri et al. (2023), who showed that blockchain adoption in Iranian auditing faced organizational resistance despite its recognized potential. Similarly, Noori Doabi et al. (2024) confirmed that consensus-building is essential for overcoming uncertainty in adopting blockchain in accounting systems. The alignment of these studies with our findings underscores the importance of culture and institutional readiness in shaping the trajectory of IT adoption.

Overall, the discussion demonstrates that the empirical results not only validate established theories such as TAM, UTAUT-2, and TOE but also extend them by incorporating sustainability-oriented constructs. By confirming the significance of factors such as sustainability pressure, auditor reputation, and environmental responsibility, the study advances a holistic model of IT adoption in auditing. This contributes to bridging the gap between traditional efficiency-focused frameworks and sustainability-oriented governance demands [3, 4, 19].

Despite its contributions, the study is not without limitations. First, it was conducted in a specific national context (Iran), which may limit the generalizability of findings to other countries with different institutional, cultural, or regulatory frameworks. Second, the study employed self-reported data through surveys, which may introduce biases such as social desirability or overestimation of IT adoption levels. Third, while the study validated twelve constructs, it did not directly measure long-term sustainability outcomes, such as reductions in carbon emissions or improvements in ESG performance. These outcomes were inferred conceptually, leaving room for empirical testing in future research. Finally, technological adoption is a rapidly evolving domain, and the findings may be affected by emerging innovations that were not captured during the research timeframe.

Future studies should seek to replicate and extend this research in other contexts, including both developed and developing economies, to compare cultural and institutional differences in IT adoption. Longitudinal designs are recommended to capture the evolving impact of IT adoption on sustainability outcomes, particularly in measuring environmental and social dimensions. Future research should also incorporate case studies and experimental methods to explore causal mechanisms between IT adoption and sustainability performance. Additionally, future work could investigate the role of global standards, such as those promoted by the International Auditing and Assurance Standards Board (IAASB), in shaping IT adoption. Finally, there is scope for examining interdisciplinary perspectives by integrating insights from information systems, sustainability science, and organizational behavior into auditing research.

For practitioners, the results highlight the importance of investing in both technology and human capital. Audit firms should prioritize continuous training programs to enhance auditors' digital competencies, while policymakers should create enabling environments through supportive regulations and incentives. Organizations should also focus on fostering a culture of innovation and sustainability, ensuring that technology adoption is aligned with broader strategic goals. Furthermore, firms should strengthen data security frameworks to mitigate risks associated with digital auditing. Collectively, these practical measures can enable auditors to become not only guardians of financial accountability but also key contributors to sustainable development governance.

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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