

## Prioritizing the Factors Influencing Sustainability Reporting Audit Risk Using Fuzzy Delphi Analytic Hierarchy Process (FDAHP)<sup>1</sup>

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### Abstract

Sustainability reporting audit risk refers to the probability that the auditor fails to detect material misstatements or errors in an organization's sustainability reports and consequently issues an inappropriate opinion. Accordingly, the present study aims to identify and prioritize the components influencing this risk and to provide practical recommendations and strategies for controlling or reducing these risks. This research adopts a mixed-methods (qualitative-quantitative) approach. In the qualitative phase, using Grounded Theory, 12 experts in the field of sustainability reporting were identified, and in-depth interviews were conducted with them. The obtained data were categorized into six domains: core phenomenon, causal conditions, intervening conditions, contextual conditions, strategies, and consequences. In the quantitative phase, the Fuzzy Delphi Analytic Hierarchy Process (FDAHP) was employed to prioritize the identified components. Using the snowball sampling method, 35 experts were selected, and the components derived from the Grounded Theory analysis were provided to them. After three rounds of expert evaluations and assessing the consensus criterion, the prioritization of components was completed. The results indicate that factors such as data reliability and technological changes (causal conditions); auditors' skills for developing sustainability reporting audits and overreliance on artificial intelligence (intervening conditions); technological advancements and legal factors (contextual conditions); understanding AI algorithms and employing appropriate audit methods (strategies); and, ultimately, enhancing data reliability and mechanizing reporting processes (consequences) were identified by experts as key determinants of sustainability reporting audit risk. Finally, practical recommendations for improving these influential factors were presented.

**Keywords:** Audit Risk, FDAHP Method, Grounded Theory, Sustainability Reporting, Sustainability Reporting Audit Risk.

**JEL Classification:** M42, M14, O33.

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## 1. Introduction

In recent decades, the importance of sustainability reporting has rapidly increased world wide, including in Iran. This type of reporting, which encompasses the disclosure of environmental, social, and governance (ESG) performance, has become one of the essential components of transparency and enhanced stakeholder decision-making. Sustainability reporting reflects a company's environmental, social, and economic achievements and demonstrates how the organization integrates these considerations into its future development plans (Global Reporting Initiative, 2022). As one of the most influential tools for corporate transparency and accountability, sustainability reporting has gained a significant position within global economic and financial systems. These reports, by focusing on environmental, social, and governance dimensions, aim to provide a comprehensive picture of organizational performance beyond financial results.

With the rise of regulatory requirements and growing stakeholder expectations, the accuracy and credibility of such reports have become critical. In this context, the role of auditing in providing assurance on the content of sustainability reports is highly significant. Any incomplete, exaggerated, or even misleading disclosure, such as the phenomenon of greenwashing, can weaken public trust and expose the organization to substantial risks regarding its credibility and sustainability. Domestic studies, such as Rahmanipour and Jalilvand (2025), indicate that sustainability reporting has considerable positive effects, including significantly reducing corporate risk and enhancing financial transparency. These findings suggest that the quality and reliability of sustainability reports can directly influence the decision-making processes of investors and other stakeholders.

Nevertheless, the non-financial nature of many sustainability indicators and the absence of uniform standards in some countries have created serious challenges for auditing such reports. International research also highlights the importance of assurance in this domain. For example, studies by Rawat et al. (2025) and Farooq and de Villiers (2019) confirm the essential role of independent auditors in validating companies' environmental and social performance. Similarly, the work of Ong et al. (2025) offers solutions for mitigating greenwashing risk through advanced ESG data analysis methods. Furthermore, the findings of Quick and Inwinkl (2020) show that auditor independence and specialized expertise in environmental and climate-related fields can substantially improve the assurance quality of sustainability reports. Complementing these insights, Deloitte (2024) notes that in many companies, chief financial officers bear the primary responsibility for sustainability reporting, yet frequently face

data-quality challenges, underscoring the necessity of designing rigorous audit mechanisms aligned with global standards.

In Iran, although the importance of sustainability reporting and its role in corporate transparency and social image are acknowledged, a comprehensive and localized framework covering economic, social, and environmental dimensions has yet to be developed. Existing reporting models are often adapted from foreign frameworks and therefore lack full alignment with the country's cultural, economic, and institutional context. In addition, both auditors and organizations have limited practical experience in non-financial aspects of sustainability reporting, and no formal national framework has been established for providing assurance on such reports. The role of emerging technologies, such as artificial intelligence, in reducing sustainability reporting risks also remains insufficiently examined and localized within the Iranian context. Moreover, the absence of clear national standards for disclosing non-financial indicators increases the risk of stakeholders misinterpreting companies' performance. Ultimately, the gap between societal expectations and organizational capabilities in meeting sustainable development requirements represents one of the major obstacles to achieving effective sustainability reporting in Iran.

Considering these challenges, the present study aims to identify and prioritize the components influencing sustainability reporting audit risk from the perspective of experts in the field.

#### **Audit Risk**

One of the essential processes in auditing is the assessment of audit risk. Audit risk refers to the probability that a material misstatement exists in the financial statements and the auditor unknowingly fails to modify their opinion accordingly. In other words, it is the likelihood that the auditor inadvertently issues an inappropriate opinion on financial statements that contain material errors.

#### **Types of Audit Risk**

**Alpha Risk (Incorrect Rejection):** This occurs when the financial statements are fairly and appropriately presented, yet the auditor issues an adverse or qualified opinion. This type of risk raises serious concerns about the auditor's efficiency and cost-effectiveness.

**Beta Risk (Incorrect Acceptance):** This occurs when the financial statements are not fairly presented, but the auditor issues an unqualified opinion. This risk calls into question the auditor's effectiveness.

#### **The Necessity of Sustainability Reporting**

With the growing need for information about the activities of business entities, traditional financial statements alone are no longer sufficient to meet the information requirements of users (Vadi'i et al; 2013). As business activities continue to expand globally, reliance on conventional accounting systems has made it increasingly difficult to measure and assess the external impacts of organizational operations. Traditional accounting systems evaluate corporate performance from limited perspectives and therefore cannot adequately capture environmental and social effects.

One of the most essential solutions for addressing these informational needs is sustainability reporting. A sustainability report provides organizational information regarding economic, environmental, social, and corporate governance performance (Mehrani et al; 2017). The shift from traditional reporting toward the disclosure of sustainability information aims to enhance transparency, strengthen brand value, improve corporate reputation and legitimacy, support benchmarking against competitors, signal competitiveness, motivate employees, and reinforce control and informational processes (Herzig & Schaltegger, 2006).

In other words, as global business activities accelerate, traditional accounting systems increasingly fail to measure or reflect the external environmental and social consequences of organizational operations.

### **The Role of Artificial Intelligence in Sustainability Reporting and Risk Management**

Modern accounting methods must adapt to various emerging factors and complexities. Technological advancements have transformed business operations, making the use of automation, artificial intelligence (AI), and data analytics essential within accounting processes. The increasing complexity of contemporary business structures, such as cross-border transactions and digital assets, requires accounting methods capable of accurately recording, analyzing, and reporting these activities.

According to recent reports, these advancements have been facilitated through three distinct forms of artificial intelligence (Munoko et al; 2020).

The first category, known as "Assisted AI Systems," involves AI technologies that replicate tasks currently performed by humans in order to support decision-making or respond to various situations. These systems typically operate based on predefined protocols. Under this approach, humans make decisions while machines execute them. The term "mechanical intelligence" refers to AI systems capable of performing routine activities (Munoko et al; 2020).

The second category, referred to as "Augmented AI Systems," involves robots or intelligent systems that carry out tasks while requiring joint human and machine decision-making. These systems are known for their "analytical intelligence," as they can interact with their environment and

acquire knowledge from auditors (Guang-Huan, 2017). In this context, AI and auditors collaborate to enhance decision-making. As a result, businesses can now achieve goals that were previously unattainable through traditional methods (Munoko et al; 2020).

The third category includes “Autonomous AI Systems.” These systems are capable of adapting to diverse situations and operating independently without auditor involvement (Kokina & Davenport, 2017). In such scenarios, the auditor delegates the decision-making process to the AI system. Autonomous AI exhibits both “intuitive intelligence” and “empathetic intelligence.” Through intuitive intelligence, AI adapts creatively and efficiently to new conditions. Empathetic intelligence enables AI to recognize human emotions, respond appropriately, and influence individuals (Munoko et al; 2020).

This section examined the interrelationship between sustainability reporting, artificial intelligence, and risk management, demonstrating how these three domains can collectively enhance organizational performance. Their interaction is complementary and simultaneous. Sustainability reporting provides the essential data required for effective risk management. Artificial intelligence analyzes these data, generating valuable insights that enhance both reporting practices and risk management processes. Risk management supports sustainability performance by identifying, assessing, and mitigating potential threats.

Overall, the integration of sustainability reporting, artificial intelligence, and risk management establishes a unified framework for enhancing organizational performance in ESG domains. Through AI-enabled technologies, organizations can produce more accurate sustainability reports, manage risks more effectively, and ultimately achieve their sustainability objectives. This synergy not only benefits organizations but also contributes to the development of a more sustainable and responsible economy.

## 2. Literature Review

Hammoud et al. (2025) conducted a study and concluded that examining the capacities, barriers, and acceptance indicators of artificial intelligence within internal auditing processes can significantly enhance audit quality and anomaly detection.

Azizi (2025) found that the key drivers influencing artificial intelligence penetration into the auditing profession and its resulting implications can clarify audit objectives and evidence. Moreover, artificial intelligence can directly contribute to reducing sustainability reporting audit risks through intelligent tools.

Izadmanan et al. (2024) concluded that field evidence demonstrates substantial changes in reporting and auditing methods, particularly through

data mining and deep learning, and their visible impact on reducing errors and sustainability reporting risks.

Sarraf and Farhangian (2022) found that five major components play a central role in explaining artificial intelligence applications in accounting, including expert systems, neural networks, genetic algorithms, fuzzy logic, and machine learning.

Khaleghizadeh Dehkordi et al. (2022) examined financial information from 139 firms during 2009 to 2018 using genetic algorithms and neural network approaches. Their findings indicate that risk management criteria significantly influence investment efficiency, and that neural-network-based artificial intelligence methods possess greater forecasting power than genetic-algorithm-based approaches for investment efficiency in listed firms.

Pazouki et al. (2021) examined the application of artificial intelligence in identifying performance factors affecting financial health. Their results show that artificial intelligence algorithms possess more than 31 percent predictive power in assessing firms' financial health. Among financial performance indicators, firm growth, return on assets, sales growth, and the ratio of current assets to total assets exert the strongest explanatory power.

The International Monetary Fund (IMF, 2024), in its assessments on strengthening the digital economy, highlights the increasing importance of regional and international cooperation and knowledge sharing. Such collaboration facilitates coordinated actions to support the safe deployment of AI and machine learning systems and allows the exchange of experiences and expertise. Ensuring access for less-developed economies to knowledge regarding techniques, use cases, and regulatory approaches is considered particularly crucial.

The World Wildlife Fund (WWF, 2024) evaluated corporate climate-transition plans by examining the integration of artificial intelligence and domain expertise. Their findings show that a comprehensive set of indicators and an NLP-based tool were developed to automate the assessment of corporate emissions-reduction plans, demonstrating how combining artificial intelligence with expert domain knowledge can reduce data gaps and risks associated with inaccurate reporting.

Dimmelmeier et al. (2024) demonstrate that textual extraction methods, including NLP, large language models, and retrieval-augmented generation, applied to sustainability reports can be effectively used for climate-risk analysis. They also discuss challenges related to the validation of extracted data and the regulatory implications, emphasizing the relevance of such reports for risk assessment and assurance.

Nichole et al. (2024) explain how artificial intelligence applications, including natural language processing, external data analytics, and big data

processing, can enhance the effectiveness and efficiency of ESG assurance processes. The study provides practical insights for auditors and regulators and directly relates to sustainability reporting audit risk from an artificial intelligence-based perspective.

Abu-Mousa et al. (2023) found that developing the necessary infrastructure for expanding artificial intelligence applications supports the achievement of sustainability goals, particularly within the context of national development strategies. The authors emphasize that specialized seminars and training workshops introducing artificial intelligence techniques and their components can enhance awareness among accounting and auditing professionals.

Brugger et al. (2023) concluded that, conceptually, the challenge of defining what sustainability information should be identified persists due to ambiguous regulatory frameworks. Their analysis examined the scope and depth of corporate reporting across the human rights management cycle.

### **3. Research Methodology**

The present study employs a mixed-method (qualitative–quantitative) research design. In the qualitative phase, which was conducted using the Grounded Theory approach (Strauss & Corbin, 1998), in-depth interviews were carried out with 12 experts selected through the snowball sampling method. The experts were chosen based on criteria including holding at least a master's degree, occupying organizational positions above deputy CEO, having more than 10 years of professional experience, and in some cases being faculty members at public or private universities.

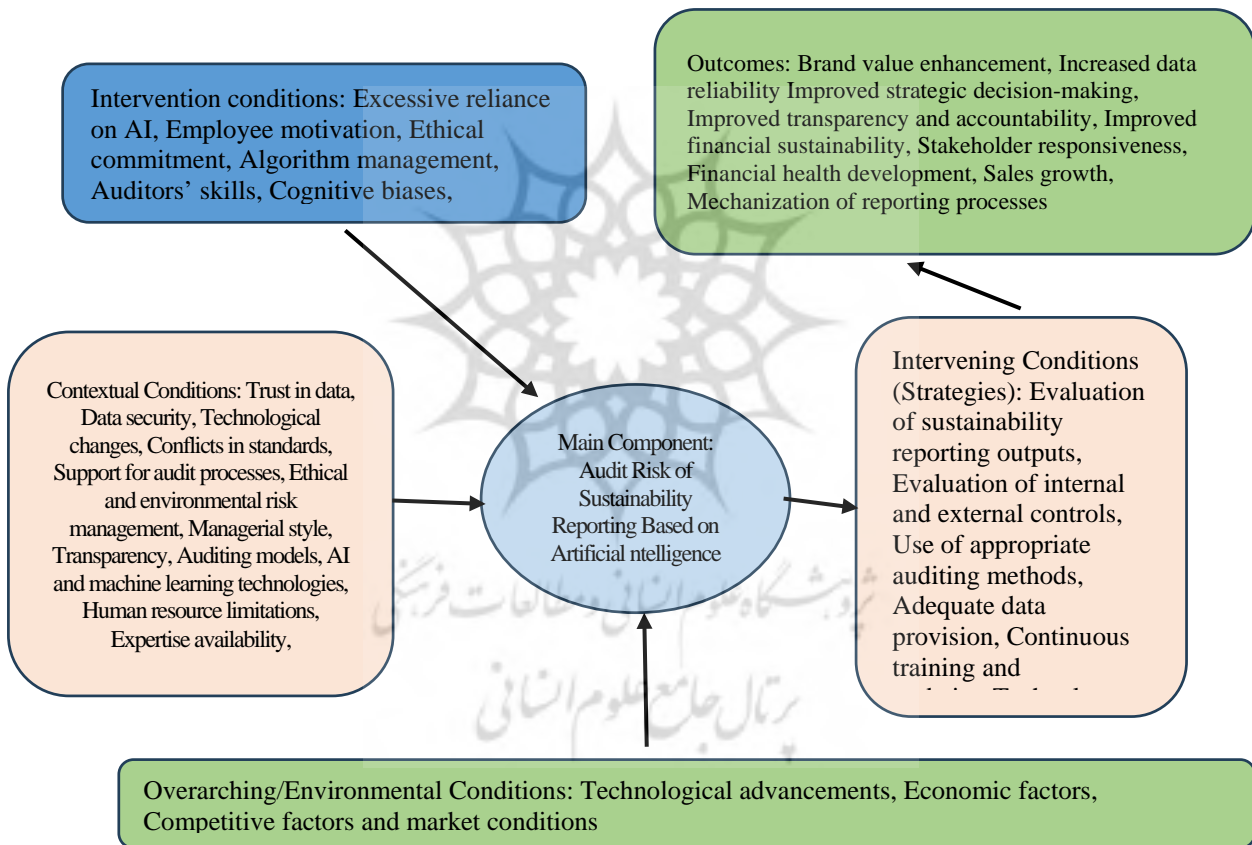
The first round of interviews was conducted in an open-ended format, and subsequent sessions, after identifying relevant themes, were carried out in a semi-structured manner. After completing the interviews, data were analyzed using the three coding stages (open, axial, and selective coding), and the MAXQDA software was used to categorize the components influencing audit risk in sustainability reporting from the experts' perspectives into six dimensions: core phenomenon, causal conditions, intervening conditions, contextual conditions, strategies, and consequences. This process ultimately led to the development of the initial conceptual framework of the research model.

In the quantitative phase, in order to prioritize the identified components, 35 experts were selected using the snowball sampling method. A Fuzzy Delphi Hierarchy questionnaire was distributed in three iterative rounds, in which the experts were asked to rate the importance of each component on a scale from 1 to 5. After the fuzzy numbers exceeded the average threshold, the consensus condition was evaluated, confirming that more than 70% agreement existed among the experts. Once consensus was

achieved, the prioritization of components was carried out step by step. Finally, based on the findings, the key components were identified.

#### 4. Data Analysis

In the qualitative phase, through interviews with 12 experts and using the Strauss and Corbin approach of Grounded Theory (Strauss & Corbin, 1998), verbal statements were initially categorized through open coding. After refining the data, a total of 229 verbal propositions were identified. These propositions were then grouped into 44 categories, which were subsequently reviewed and refined by experts during the axial and selective coding stages. Ultimately, based on the finalized categories and main themes, the configuration of the research model was derived and is presented in Figure 1.



*Figure 1. Initial Model Extracted from Grounded Theory*

In the quantitative phase, the Fuzzy Delphi Analytic Hierarchy Process (FDAHP) was employed for prioritization. Initially, 53 experts were identified through the snowball sampling method and were contacted to participate in the quantitative stage. Ultimately, 35 experts completed and returned the distributed questionnaires. The results derived from the analysis of these 35 questionnaires are presented in Table 1.

**Table 1. Aggregated Expert Opinions for the First-Round Questionnaire**

Dimensions	Question Number	Questions	Importance Scale				
			Very Low (1)	Low (2)	Medium (3)	High (4)	Very High(5)
Governing Context	q1	Technological advancements		2	2	10	21
	q2	Economic factors	8	9	10	4	4
	q3	Competitive and market factors	7	12	5	6	5
	q4	Environmental factors			5	9	21
	q5	Political factors		2	4	6	23
	q6	Cultural factors		2	6	9	18
	q7	Legal factors		7	2	7	19
Outcomes	q8	Brand value enhancement	3	15	4	4	9
	q9	Increased data reliability		1	4	8	22
	q10	Improved strategic decision-making	9	14	4	5	3
	q11	Improved transparency and accountability		4	4	8	19
	q12	Improved financial	6	12	6	7	4

Dimensions	Question Number	Questions	Importance Scale				
			Very Low (1)	Low (2)	Medium (3)	High (4)	Very High(5)
Dimensions		sustainability performance					
	q13	Stakeholder responsiveness		2	4	9	20
	q14	Financial health development		1	3	7	24
	q15	Sales growth	2	4	5	7	17
	q16	Mechanization of reporting processes		2	4	12	17
	Strategies	q17	Evaluation of sustainability reporting output controls	7	11	3	9
q18		Evaluation of internal controls		3	6	9	17
q19		Use of appropriate auditing methods		2	5	9	19
q20		Awareness of audit data	8	14	7	3	3
q21		Continuous training and updating		2	6	8	19
q22		Technological innovation development		2	4	8	21
q23		Understanding of AI algorithms		1	3	16	15
q24		Risk management		7	3	6	19
q25		Explainable artificial intelligence		2	3	3	27
Causal Conditions	q26	Data trustworthiness		1	4	8	22

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Dimensions	Question Number	Questions	Importance Scale				
			Very Low (1)	Low (2)	Medium (3)	High (4)	Very High(5)
Dimensions	q27	Cybersecurity	8	15	6	3	3
	q28	Technological changes		3	6	9	17
	q29	Standard inconsistencies	8	10	7	6	4
	q30	Support for control processes		3	4	10	18
	q31	Ethical and environmental risks		3	7	7	18
	q32	Management style	8	13	5	4	5
	q33	Transparency of audit models		2	4	5	24
	q34	Machine learning technologies		2	5	7	21
	q35	Limited specialized human resources		4	4	12	15
	q36	Incentives	7	14	5	5	4
Intervening Conditions	q37	Overreliance on AI		3	6	11	15
	q38	Employee motivation		2	7	12	14
	q39	Ethical commitment		1	3	13	18
	q40	Algorithmic bias	8	9	9	5	4
	q41	Change management		1	7	13	14
	q42	Auditor skills		4	7	10	14
	q43	Attitude	7	11	9	3	5
	q44	Mental norms		2	3	11	19

Based on the table above, the fuzzy value of each expert’s response for each question was calculated and presented in Table 2. To determine whether the components were approved by the experts, those with a value below the average threshold of 3 were eliminated.

**Table 2. Fuzzy Values and Defuzzified Scores of the First-Round Questionnaire Items**

Approval Status	Defuzzified Value	Fuzzy Value of Each Questionnaire Item			question
		U	M	L	
Approved	3.61	5	3.833333	2	q1
Not Approved	2.93	5	2.782609	1	q2
Not Approved	2.91	5	2.73913	1	q3
Approved	4.00	5	4	3	q4
Approved	3.53	5	3.6	2	q5
Approved	3.53	5	3.6	2	q6
Approved	3.59	5	3.777778	2	q7
Not Approved	2.84	5	2.521739	1	q8
Approved	3.56	5	3.666667	2	q9
Not Approved	2.87	5	2.608696	1	q10
Approved	3.56	5	3.666667	2	q11
Not Approved	2.93	5	2.8	1	q12
Approved	3.56	5	3.692308	2	q13
Approved	3.57	5	3.7	2	q14
Approved	3.06	5	3.1875	1	q15
Approved	3.58	5	3.75	2	q16
Not Approved	2.97	5	2.913043	1	q17
Approved	3.53	5	3.6	2	q18
Approved	3.55	5	3.642857	2	q19
Not Approved	2.85	5	2.541667	1	q20
Approved	3.52	5	3.571429	2	q21
Approved	3.56	5	3.666667	2	q22
Approved	3.61	5	3.842105	2	q23
Approved	3.56	5	3.666667	2	q24
Approved	3.50	5	3.5	2	q25
Approved	3.56	5	3.666667	2	q26
Not Approved	2.83	5	2.5	1	q27

Approval Status	Defuzzified Value	Fuzzy Value of Each Questionnaire Item			question
		U	M	L	
Approved	3.53	5	3.6	2	q28
Not Approved	2.94	5	2.826087	1	q29
Approved	3.57	5	3.714286	2	q30
Approved	3.50	5	3.5	2	q31
Not Approved	2.86	5	2.590909	1	q32
Approved	3.52	5	3.555556	2	q33
Approved	3.53	5	3.583333	2	q34
Approved	3.58	5	3.75	2	q35
Not Approved	2.88	5	2.625	1	q36
Approved	3.55	5	3.647059	2	q37
Approved	3.54	5	3.631579	2	q38
Approved	3.60	5	3.8125	2	q39
Not Approved	2.94	5	2.826087	1	q40
Approved	3.55	5	3.65	2	q41
Approved	3.53	5	3.588235	2	q42
Not Approved	2.88	5	2.652174	1	q43
Approved	3.60	5	3.785714	2	q44

Subsequently, in the second round, the approved components were presented to the experts again, and they were asked to suggest any additional components if applicable. The procedures of this phase were similar to those in the first round. In this round, the questionnaire items Q2, Q3, Q8, Q10, Q12, Q17, Q20, Q27, Q29, Q32, Q36, Q40, and Q43 fell below the predetermined threshold and were thus eliminated, while the remaining items exceeded the threshold and were approved.

In the third round, the validated items from the second round were again distributed to the experts. It is noteworthy that in this phase, six items (Q3, Q10, Q12, Q23, Q25, and Q31) had defuzzified values below the average of the evaluation scale (i.e; 3) and were therefore removed. Ultimately, 25

items remained and were sent to the panel members for the third round of the Fuzzy Delphi process. The final results are presented in Table 3.

After evaluating the consensus condition and expert agreement, the defuzzified values of all items were found to be above the average threshold of 3, which satisfies the stopping criterion. Consequently, the 25 items were confirmed as the main components influencing sustainability reporting audit risk. Furthermore, the consensus condition was examined, and since agreement exceeded 70% for all items except one (Explainable AI), it can be concluded that the identified audit risk components were generally agreed upon by the experts.

**Table 3. Evaluation of Expert Consensus or Agreement**

Questions	Fuzzy value of each question			Defuzzified value of each question	Maximum aggregated value	Level of consensus	Consensus status
	L	M	U				
Technological advancements	2	3.8	5	3.6	29	86.6667	Consensus reached
Environmental factors	2	3.833	5	3.611	28	86.19048	Consensus reached
Cultural factors	2	3.75	5	3.583	25	82.61905	Consensus reached
Legal factors	2	3.6	5	3.533	24	82.14286	Consensus reached
Increased data reliability	2	3.5	5	3.5	27	82.85714	Consensus reached
Improved transparency and accountability	2	3.714	5	3.571	26	83.09524	Consensus reached
Stakeholder responsiveness	2	3.778	5	3.593	25	84.04762	Consensus reached
Financial health development	2	3.7	5	3.567	23	80.95238	Consensus reached
Mechanization of reporting processes	2	3.714	5	3.571	27	85	Consensus reached
Use of appropriate auditing methods	2	3.727	5	3.576	22	80.47619	Consensus reached
Continuous training and updating	2	3.714	5	3.571	26	83.09524	Consensus reached
Technological innovation development	3	4	5	4	30	87.85714	Consensus reached
Understanding of AI algorithms	2	3.5	5	3.5	25	81.19048	Consensus reached
Risk management	3	4	5	4	30	87.85714	Consensus reached

Questions	Fuzzy value of each question			Defuzzified value of each question	Maximum aggregated value	Level of consensus	Consensus status
	L	M	U				
Explainable artificial intelligence	2	3.591	5	3.53	13	69.04762	No consensus
Data trustworthiness	2	3.714	5	3.571	27	85	Consensus reached
Technological changes	2	3.75	5	3.583	25	82.61905	Consensus reached
Support for control processes	2	3.7	5	3.567	22	79.04762	Consensus reached
Ethical and environmental risks	2	3.625	5	3.542	25	81.90476	Consensus reached
Machine learning technologies	2	3.5	5	3.5	23	79.52381	Consensus reached
Overreliance on AI	3	4	5	4	31	88.33333	Consensus reached
Employee motivation	2	3.714	5	3.571	20	80.2381	Consensus reached
Ethical commitment	1	3.353	5	3.118	17	73.33333	Consensus reached
Change management	2	3.8	5	3.6	29	86.66667	Consensus reached
Auditor skills	2	3.667	5	3.556	28	85.47619	Consensus reached

As shown in the table above, out of a total of 25 questions in the final phase of the fuzzy Delphi process, one question—related to explainable artificial intelligence—did not reach an overall consensus among the experts. All other questions achieved an expert consensus level exceeding 70%, indicating that the respondents reached agreement and convergence, and the consensus rate for each of the remaining items was above 70%. Therefore, based on the research team’s criteria, the consensus threshold for the third-round questionnaire is considered to be met.

Given the results, namely that the questions achieved the predefined consensus threshold and no new components were removed or added, it is evident that the agreement condition required for the study has been satisfied. Furthermore, as the stopping criterion was reached, the key remaining components were listed for use in the next stage of the research, which involves assessing the feasibility of audit risk in AI-based sustainability reporting.

Ultimately, considering the fuzzy Delphi procedures conducted and the perspectives of experts in AI-driven sustainability reporting audit risk, the refined research model is as follows:

Subsequently, after identifying the components, their prioritization was carried out in the following stages.

**A) Construction of Pairwise Comparison Matrices Based on Expert Opinions**

In this stage, the identified components were first grouped according to their relevant dimensions. Then, within each group, the key and priority components were determined separately. For this purpose, a square matrix was created for each group, containing n components extracted from the expert consensus (where n is the number of components in that group). Experts were asked to provide their judgments regarding the relative importance of each component compared to the others.

Next, the expert opinions were expressed in fuzzy numbers, defined by lower, middle, and upper bounds, and the average fuzzy numbers were calculated.

Considering that the research model comprised five main dimensions (causal conditions, intervening conditions, contextual conditions, strategies, and consequences), the effective components within each dimension were prioritized. An example from one dimension is presented below. It should be noted that the other dimensions were prioritized in the same manner.

**Causal Conditions**

First, the average fuzzy numbers of expert opinions regarding the five final components were calculated, as shown in Table 4.

*Table 4. Average Fuzzy Numbers for Causal Conditions*

Causal Condition	Category One	Category One	Category One	Category Two	Category Two	Category Two	Category Three	Category Three	Category Three	Category Four	Category Four	Category Four	Category five	Category five	Category five
Category One	1.00	1.00	1.00	1.44	1.23	1.48	1.32	0.78	1.00	0.61	2.74	2.12	1.03	1.28	1.17
Category Two	0.70	0.82	0.68	1.00	1.00	1.00	2.12	1.46	1.99	2.36	1.93	2.47	2.67	2.24	2.49
Category Three	0.76	1.28	1.00	0.47	0.69	0.50	1.00	1.00	1.00	0.85	1.63	1.43	1.63	2.51	0.71
Category Four	1.63	0.37	0.47	0.42	0.52	0.41	1.18	0.61	0.70	1.00	1.00	1.00	1.91	1.29	1.07
Category five	0.97	0.78	0.85	0.37	0.45	0.40	0.61	0.40	1.42	0.52	0.77	0.93	1.00	1.00	1.00

After constructing the fuzzy pairwise comparison matrix, the next step was to determine the fuzzy weights of the components (denoted as  $Z_i$ ), the values of which are presented in Table 5.

**Table 5. Fuzzy Weights of the Components for Causal Conditions**

	u	m	l
z1	1.30	1.27	1.04
z2	1.53	1.39	1.56
z3	0.87	1.29	0.87
z4	0.68	0.68	1.09
z5	0.85	0.64	0.65

Finally, after determining the defuzzified weights of the components ( $W_i$ ), the importance of each research component was established. The results are presented in Table 6 and Table 7.

**Table 6. Defuzzified Weights and Ranking of Components**

$W_i$	U	M	L
sum of $Z_i$	5.23	5.28	5.21
w1	0.25	0.24	0.20
w2	0.29	0.26	0.30
w3	0.17	0.24	0.17
w4	0.13	0.13	0.21
w5	0.16	0.12	0.12

**Table 7. Priority Ranking of Components for Causal Conditions**

Component Title	Defuzzified weight	Rank
Technological Changes	0.41	2
Data Reliability	0.47	1
Support for Control Processes	0.37	3
Ethical and Environmental Risks	0.32	4
Machine Learning Technologies	0.30	5

As shown in the above table, according to the experts, the most important causal factor influencing the AI-based sustainability reporting audit risk is trust in data, followed by technological changes.

**Intervening Conditions:**

Similar to the prioritization process for causal conditions, the calculations for intervening conditions were also carried out, with the final results presented in Table 8.

*Table 8. Priority Ranking of Components for Intervening Conditions*

Component Title	Defuzzied weight	Rank
Auditors' Skills	0.48	1
Overreliance on Artificial Intelligence	0.43	2
Change Management	0.39	3
Employee Motivation	0.31	4
Ethical Commitment	0.27	5

As shown in the above table, according to the experts, the most important intervening condition affecting AI-based sustainability reporting audit risk is the auditors' skills for developing sustainability reporting audits, followed by overreliance on artificial intelligence.

**Contextual Conditions:**

Similar to the prioritization process for the previous factors, the same procedure was applied to contextual conditions, with the final results presented in Table 9.

*Table 9. Priority Ranking of Components for Contextual Conditions*

Component Title	Defuzzied weight	Rank
Technological Advancements	0.607	1
Legal Factors	0.314	2
Cultural Factors	0.128	4
Environmental Factors	0.276	3

As shown in the above table, according to the experts, the most important contextual condition (governing environment) affecting AI-based

sustainability reporting audit risk is technological advancements, followed by legal factors.

**Strategies or Actions:**

Similar to the prioritization process of the previous factors, the prioritization of strategies for the successful implementation and execution of sustainability reporting audit risk was carried out, with the final results presented in Table 10.

*Table 10. Priority Ranking of Strategy Components*

Component Title	Defuzzied weight	Rank
Risk Management	0.33	5
Familiarity with Artificial Intelligence Algorithms	0.412	1
Use of Appropriate Auditing Methods	0.392	2
Technological Innovation Development	0.353	4
Continuous Training and Updating	0.373	3

As shown in the above table, according to the experts, the most important strategy is familiarity with artificial intelligence algorithms in addressing AI-based sustainability reporting audit risk, followed by the use of appropriate auditing methods.

**Outcomes**

Similar to the prioritization process of previous factors, the prioritization of outcomes resulting from strategies to control sustainability reporting audit risk was carried out, with the final results presented in Table 11.

*Table 11. Priority Ranking of Outcome Components*

Component Title	Defuzzied weight	Rank
Improving Transparency and Accountability	0.359	3
Enhancing Data Reliability	0.445	1
Stakeholder Responsiveness	0.350	4
Mechanization of Reporting Processes	0.404	2
Financial Health Development	0.260	5

As shown in the above table, according to the experts, in terms of feasibility assessment of the AI-based sustainability reporting audit risk model for enhancing auditing and sustainability reporting, the most important outcomes are enhancing data reliability, followed by the mechanization of reporting processes.

## **5. Conclusion and Recommendations**

Sustainability reporting, as a managerial and informational tool aimed at identifying and measuring the economic, social, and environmental impacts of an organization's activities, has gained significant importance. In recent decades, such reports have become one of the key pillars for evaluating the performance of companies and organizations. In this context, the use of artificial intelligence (AI) for data collection, analysis, and the generation of sustainability reports offers numerous advantages, including higher accuracy, faster data processing, and the ability to analyze complex and large-scale datasets.

### **Practical Recommendations Based on the Prioritization Results of the Study**

To reduce the audit risk of sustainability reporting, the first step is to focus on the most critical causal factor, which is trust in data. This can be achieved through the implementation of robust internal control systems, the use of data validation methods, and ensuring transparency in data collection. Subsequently, preparedness for technological changes is essential; given the rapid growth of digital tools, organizations must equip their infrastructure and cultivate an organizational culture ready to adopt emerging technologies.

In the domain of intervening conditions, enhancing auditors' skills takes precedence. These skills include the ability to analyze complex datasets, understand AI models, and leverage digital tools within the auditing process. Alongside this, overreliance on AI should be avoided, as it may lead to the neglect of professional judgment and critical analysis.

Within the contextual conditions, technological advancements are identified as the primary factor. Utilizing software, intelligent platforms, and modern technologies can improve both the speed and accuracy of auditing processes. Legal factors are the next most significant element; adherence to national and international standards ensures that sustainability reporting remains reliable and credible.

Regarding strategies, emphasis should first be placed on the precise understanding of AI algorithms, as comprehension of these algorithms enables auditors to better identify potential risks. Following this, the application of appropriate auditing methods, such as data-driven audits and advanced analytical procedures, strengthens the overall effectiveness of the process.

Finally, these measures yield positive outcomes. Enhancing data reliability allows decision-makers and stakeholders to rely on reports with greater confidence. Additionally, the mechanization of reporting processes saves time, reduces human error, and improves operational efficiency in auditing.

The findings of this study are consistent with previous research concerning factors such as expert systems, neural networks, genetic algorithms, fuzzy logic, machine learning, risk management criteria, investment efficiency, fraud detection and investigation, infrastructure development, expansion of AI applications, seminars and workshops, introduction of AI techniques, and awareness-raising (Sarraf & Farhangian, 2022; Khaleghizadeh Dehkordi et al; 2022; Pazouki et al; 2021; Saeedabadi et al; 2021; Abumousa et al; 2023; Brugger et al; 2023; Liao et al; 2022). These efforts align with the current study's aim of better identifying the components of audit risk in sustainability reporting, indicating a significant step forward in this field.



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