Developing a Model of Dynamic Interaction between Auditors and Artificial Intelligence Systems in the Audit Process

Mohammad Dehghani Starki[1], Hossein Jabbari [2,*], Hassan Ghodrati [3], Ali Akbar Farzinfar [4] and Mohammad Reza Mohagheghi [5]



[1] Department of Accounting, Kas.C., Islamic Azad University, Kashan, Iran;
[2] Department of Accounting, Kas.C., Islamic Azad University, Kashan, Iran;
[3] Department of Accounting, Kas.C., Islamic Azad University, Kashan, Iran;
[4] Department of Accounting, Kas.C., Islamic Azad University, Kashan, Iran;
[5] Department of Accounting, Kas.C., Islamic Azad University, Kashan, Iran;

* Correspondence: Jabari1352@iau.ac.ir

Citation: Dehghani Starki, M., Jabbari, H., Ghodrati, H., Farzinfar, A. A., & Mohagheghi, M. R. (2027). Developing a Model of Dynamic Interaction between Auditors and Artificial Intelligence Systems in the Audit Process . *Business, Marketing, and Finance Open*, 4(7), 1-26.

Abstract: The expansion of cognitive technologies and the increasing complexity of financial data have necessitated the transformation of audit processes. This study aimed to develop a model of dynamic interaction between auditors and artificial intelligence systems in the audit process. The study adopted a sequential exploratory approach and employed grounded theory. The study population comprised university faculty members and experts in auditing and artificial intelligence. Using purposive snowball sampling until theoretical saturation was achieved, 13 participants were selected and interviewed through semi-structured interviews. Qualitative data were analyzed through three-stage coding using MAXQDA. The resulting model demonstrated that the core phenomenon, 'dynamic and intelligent interaction between the auditor and artificial intelligence,' emerges under the influence of causal conditions (professional pressures and information complexity), contextual conditions (human capabilities, data readiness, and infrastructure), and intervening conditions (human barriers, ethical risks, and legislative gaps).

Keywords: Artificial intelligence, dynamic interaction, audit quality, grounded theory.

Received: 02 April 2026
Revised: 17 September 2026
Accepted: 24 September 2026
Initial Publication: 07 November 2026
Final Publication: 01 July 2027

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1. Introduction

The rapid expansion of artificial intelligence (AI), machine learning, advanced analytics, robotic process automation, natural language processing, and intelligent decision-support systems has fundamentally altered the technological environment in which accounting and auditing activities are performed. The increasing volume, velocity, variety, and complexity of financial and nonfinancial information have made conventional audit procedures based primarily on manual examination, limited sampling, retrospective verification, and individual professional judgment increasingly difficult to sustain as the sole foundations of assurance. Contemporary organizations generate continuous streams of transactional, operational, environmental, social, governance, and digital data that require auditors to detect patterns and anomalies within datasets far beyond the processing capacity of unaided human cognition. Consequently, AI is increasingly being incorporated into audit workflows to automate repetitive procedures, analyze large datasets, identify unusual transactions, prioritize risk areas, recognize complex patterns,

and support more timely professional decisions [1]. The emergence of AI-enabled auditing therefore represents more than the introduction of another technological instrument; it signals a broader transformation in the architecture of audit work and in the relationship between auditors, evidence, professional judgment, and intelligent systems [2].

One of the principal advantages attributed to AI in auditing is its capacity to overcome some of the limitations associated with traditional audit methods. Intelligent systems can process entire populations rather than relying exclusively on samples, continuously monitor transactions, detect deviations from expected patterns, and perform predictive analyses capable of directing auditors toward areas requiring greater professional attention. Continuous AI-based reporting, monitoring, and assurance environments can further reduce the temporal gap between the occurrence of economic events and their examination, potentially shifting auditing from periodic retrospective assessment toward more continuous forms of assurance [3]. Similarly, intelligent systems developed for dynamic business-process verification demonstrate how automated controls and continuous corporate auditing can provide near-real-time assessment of transactions and organizational activities [4]. In specialized areas such as environmental, social, and governance auditing, reinforcement-learning applications have also been proposed to improve anomaly analysis and adaptive decision-making under changing risk conditions [5]. These developments suggest that AI may substantially enhance the scope, speed, accuracy, and analytical depth of audit procedures while simultaneously transforming the evidential basis upon which professional judgments are made.

The integration of AI into auditing, however, cannot be adequately conceptualized as a simple process of replacing human labor with automated systems. Auditing is fundamentally a professional activity involving skepticism, contextual interpretation, ethical accountability, evaluation of conflicting evidence, and judgment under uncertainty. Many audit issues cannot be resolved exclusively through statistical correlations or automated classifications because the significance of evidence depends on organizational context, management incentives, regulatory requirements, materiality, professional standards, and the auditor's interpretation of circumstances. The concept of the “hybrid auditor” therefore emphasizes the integration of machine analytical capabilities with human professional judgment and ethical responsibility rather than the displacement of the auditor by technology [6]. Research on AI-enhanced audit-team performance similarly indicates that the value of intelligent systems depends substantially on how technological capabilities are combined with human expertise, coordination, learning, and judgment within audit teams [7]. More broadly, experiences from other knowledge-intensive professional domains also demonstrate that transformative AI implementation requires the integration of computational capabilities with human expertise, institutional processes, and adaptive organizational structures rather than technological deployment in isolation [8].

This complementary relationship creates a new professional problem: how should auditors and AI systems interact with one another throughout the audit process? Traditional information technologies were predominantly passive tools that executed predefined commands, stored information, or assisted users in performing established procedures. Contemporary AI systems, by contrast, can learn from data, generate recommendations, identify previously unrecognized relationships, predict risks, classify evidence, and sometimes alter their outputs as additional information becomes available. Therefore, the auditor–technology relationship is increasingly reciprocal and adaptive rather than strictly instrumental. The emerging “algorithmic auditor” operates within a socio-technical environment in which professional work results from interaction among algorithms, auditors, organizational structures, standards, data, and accountability mechanisms [9]. This transformation raises important questions concerning the allocation of tasks, degree of reliance on AI-generated results, preservation of professional

skepticism, validation of system recommendations, and responsibility for final audit conclusions. From a cybernetic perspective, effective integration further requires feedback mechanisms through which intelligent control systems and human decision-makers continually evaluate and correct one another [10]. Accordingly, the central issue is increasingly not whether AI should be used in auditing, but how an effective and professionally responsible pattern of interaction between auditors and intelligent systems can be established.

Trust constitutes a particularly important dimension of this interaction. Auditors cannot derive sustainable professional value from AI systems if they fundamentally distrust algorithmic outputs, yet excessive trust may generate automation bias and reduce the independent scrutiny required in assurance engagements. Empirical qualitative research suggests that auditors' trust in AI is conditional and is shaped by factors such as system reliability, transparency, explainability, organizational governance, previous experience, and perceived accountability [11]. Trust is therefore not equivalent to passive acceptance; it is better understood as calibrated reliance in which auditors remain capable of challenging, validating, and overriding machine recommendations. This issue is also reflected in AI-based auditing-service models emphasizing customer trust, where technological capability creates value only when stakeholders perceive intelligent audit procedures and their outputs as reliable and credible [12]. The same challenge is evident in research on auditors' judgment, which shows that intelligence, design, and choice dimensions of AI-based systems can influence professional decision processes and therefore require careful consideration of the interaction between computational recommendations and auditor judgment [13].

The successful integration of AI also depends on technology acceptance and organizational readiness. Auditors may recognize the potential usefulness of intelligent systems while remaining reluctant to incorporate them systematically because of inadequate skills, organizational resistance, implementation costs, limited infrastructure, or uncertainty concerning their professional consequences. Research applying technology–organization–environment perspectives in auditing indicates that AI acceptance is influenced by an interdependent combination of technological characteristics, organizational capabilities, and environmental pressures [14]. A broader acceptance model for AI-based financial accounting systems similarly highlights that organizational adoption is conditioned by perceptions of usefulness and feasibility as well as institutional, technical, and managerial factors [15]. System-dynamics approaches further demonstrate that AI adoption in auditing evolves over time through interacting feedback mechanisms involving organizational learning, investment, professional capabilities, perceived benefits, and implementation barriers [16]. Consequently, developing effective auditor–AI interaction requires attention not only to the technical characteristics of algorithms but also to the organizational ecosystem in which auditors encounter, evaluate, learn, and use these technologies.

Human capabilities are particularly critical because the expansion of AI changes the competency profile expected of contemporary auditors. Auditors increasingly require digital literacy, data-analytical capabilities, familiarity with algorithmic reasoning, and sufficient technical understanding to evaluate the reliability and limitations of AI-generated outputs. At the same time, professional competencies such as skepticism, ethical reasoning, contextual interpretation, and communication become more rather than less important when machine recommendations influence audit decisions. Organizational adaptation to generative AI illustrates that intelligent auditing requires dynamic capabilities through which organizations continually reconfigure knowledge, routines, skills, and technological resources in response to rapidly changing digital environments [17]. Studies of Industry 4.0 technology adoption in auditing likewise emphasize the importance of organizational, technological, professional, and environmental factors in determining whether advanced technologies can be successfully incorporated into

audit practices [18]. In the context of internal auditing, AI and electronic data processing have similarly been associated with transformation in auditors' roles and working methods, requiring stronger technological competencies and closer integration between audit and information-processing functions [19].

Alongside opportunities for improved efficiency and analytical capability, AI introduces significant technological, ethical, and operational risks. Algorithmic outputs depend on the quality, representativeness, completeness, and integrity of input data; therefore, inaccurate or biased data may generate misleading risk classifications or anomalous results. Cybersecurity is another critical concern because AI-driven auditing often requires access to large volumes of sensitive organizational and financial information. The integration of cybersecurity threat intelligence with AI-based internal audit risk assessment can improve risk identification, yet it simultaneously highlights the importance of protecting information infrastructures and ensuring that intelligent systems themselves do not become sources of vulnerability [20]. Studies examining AI in internal auditing, including within Islamic financial institutions, similarly identify data security, technological infrastructure, ethical governance, professional competencies, and system reliability as important determinants of effective AI use [21]. Research focusing on tax auditing also reports that AI adoption simultaneously creates opportunities for improved analytical efficiency and challenges involving infrastructure, expertise, interpretability, security, and implementation [22].

Ethical accountability and professional responsibility become especially complex when algorithmic recommendations directly affect audit conclusions. AI systems do not possess professional responsibility in the same sense as licensed auditors, yet their outputs may substantially influence risk assessment, evidence selection, and the direction of audit procedures. This creates potential ambiguity concerning responsibility when an intelligent system fails to identify fraud, produces a biased assessment, or recommends an inappropriate conclusion. Independent auditing applications of AI therefore require a clear distinction between technological decision support and professional decision authority [23]. Auditors must remain capable of understanding the evidential implications of AI outputs, comparing them with alternative evidence, and documenting the reasoning underlying their final judgments. A systematic review of AI and robotic process automation in accounting and auditing similarly shows that automation can improve efficiency and reduce routine workload while also generating challenges related to governance, human skills, control, accountability, and the redesign of professional roles [24]. Thus, responsible AI-enabled auditing requires a human-in-the-loop structure in which technological capability strengthens rather than substitutes professional accountability.

These challenges acquire particular importance in emerging institutional contexts, where technological development may advance more rapidly than regulatory structures, professional standards, and organizational readiness. Studies examining the auditing profession in different national contexts demonstrate that practitioners often perceive significant potential benefits from AI but simultaneously report concerns regarding skills, costs, cybersecurity, data quality, ethical issues, and unclear regulatory requirements. Evidence from the auditing profession in Jordan, for example, suggests that the perceived effects of AI encompass both improvements in audit efficiency and quality and considerable implementation challenges requiring professional adaptation [25]. Research on AI and auditing practices in municipalities likewise shows that the impact of intelligent technologies depends on the institutional setting in which auditing is conducted and on the capacity of organizations to translate technological resources into effective audit practices [26]. These findings reinforce the view that auditor–AI interaction is institutionally embedded and cannot be explained solely through the technical sophistication of the systems being used.

The Iranian auditing environment has increasingly attracted attention in this regard. Recent studies have examined multiple dimensions of AI adoption, including technological acceptance, auditor judgment, audit risk, decision-making, and the opportunities and challenges associated with intelligent technologies. A model of AI-based audit risk in sustainability reporting has emphasized the importance of integrating intelligent analytical capabilities with data quality, professional requirements, and emerging sustainability-related risks [27]. Studies examining AI-based decision-making in the audit process have also identified opportunities for increasing accuracy, speed, analytical capacity, and risk detection while simultaneously documenting concerns related to human skills, infrastructure, governance, trust, and ethical and professional constraints [28]. These challenges indicate that the transition toward AI-enabled auditing is not merely a technical modernization project; rather, it involves redefining professional routines, organizational relationships, decision processes, and the boundaries between machine-generated analysis and auditor-controlled judgment.

The need for an integrated perspective becomes even clearer when emerging-technology-based auditing is considered in relation to financial transparency and the control of economic corruption. Recent grounded-theory research has proposed integrated auditing models in which AI and network analysis provide enhanced capabilities for identifying complex financial relationships and supporting transparency, demonstrating that new technologies can transform both the informational scope and social function of auditing [29]. At the same time, such transformation intensifies the need for explicit mechanisms of control, validation, accountability, and human oversight. AI cannot independently determine the professional significance of every identified relationship, and high computational accuracy does not automatically guarantee appropriate professional interpretation. The value of emerging technologies therefore depends on the development of an interaction structure through which machine-generated findings can be interpreted and validated within the auditor's professional and institutional framework.

Current research consequently reveals an important conceptual gap. Much of the literature has examined AI from the perspectives of adoption, opportunities and barriers, audit efficiency, fraud detection, risk assessment, automation, or professional acceptance. These strands provide essential knowledge regarding what AI can contribute to auditing and which factors facilitate or inhibit its implementation. However, comparatively less attention has been devoted to the interaction process itself: how auditor judgment and intelligent analysis continuously affect one another; how trust should be calibrated; how outputs are validated; how human control is retained; how contextual and intervening conditions alter the interaction; and how reciprocal human–machine collaboration ultimately produces audit outcomes. The distinction is important because successful technology adoption does not necessarily imply successful auditor–AI interaction. An organization may possess advanced systems without developing appropriate routines for professional evaluation, feedback, responsibility, or integration into audit decision-making. Likewise, auditors may formally use AI while either relying excessively on its outputs or failing to exploit its analytical capabilities effectively.

Accordingly, a dynamic-interaction perspective provides a more comprehensive conceptual foundation than approaches treating AI merely as an independent technological input. Dynamic interaction may be understood as a reciprocal, continuous, adaptive, and feedback-oriented process in which AI contributes computational capacity, pattern recognition, anomaly detection, prediction, and analytical recommendations, while auditors contribute professional skepticism, contextual interpretation, ethical reasoning, experiential knowledge, validation, and ultimate decision responsibility. Such interaction is shaped by causal pressures arising from increasing information complexity and professional demands, contextual conditions such as human competence, data readiness and

infrastructure, and intervening conditions including resistance, cybersecurity threats, ethical risks, regulatory uncertainty, and responsibility gaps. Its effectiveness depends on strategies that preserve professional judgment while enabling intelligent risk analysis, fraud detection, full-population examination, continuous monitoring, and validation of system outputs. Understanding these relationships is necessary for moving the literature beyond the question of whether AI should be adopted toward the more consequential question of how humans and intelligent systems should cooperate within a professionally accountable audit environment.

Therefore, the aim of the present study is to develop a comprehensive model of dynamic interaction between auditors and artificial intelligence systems in the audit process by identifying its causal conditions, contextual conditions, intervening conditions, core phenomenon, interaction strategies, and professional consequences.

2. Methods and Materials

This study is exploratory in purpose and qualitative in the nature of its data, and adopts a pragmatic approach. Its primary objective is to identify and explain the dimensions and components of 'dynamic interaction between auditors and artificial intelligence systems in the audit process' and ultimately to develop a conceptual model of that interaction. To this end, the study follows inductive reasoning, and data are collected through semi-structured interviews with experts in auditing, information technology, and artificial intelligence. Participants are selected through purposive and snowball sampling, with recruitment continuing until theoretical saturation. Approximately 13 university faculty members and professional experts may constitute the participant group. Following data collection, the interviews are fully transcribed, and the data are coded and analyzed through thematic analysis using MAXQDA at three levels—basic, organizing, and global themes—to extract the model's conceptual structure. To ensure the quality and trustworthiness of the findings, Lincoln and Guba's criteria of credibility, transferability, dependability, and confirmability are applied, including participant review of results, detailed description of the research context, and comprehensive documentation of the analytical process. The final output of this stage is therefore a qualitative conceptual model explaining the dimensions, components, and relationships involved in auditor–artificial intelligence interaction.

3. Findings and Results

Table 1 presents the interviewees' demographic and professional characteristics.

Table 1. Demographic and Professional Characteristics of the Interviewees

No.	Interviewee code	Gender	Academic degree	Discipline / specialization	Position or field of activity	Relevant experience (years)
1	E1	Male	PhD	Accounting / Auditing	University faculty member and independent auditor	22
2	E2	Female	PhD	Accounting	University faculty member; auditing and technology researcher	18
3	E3	Male	PhD	Accounting / Auditing	Audit firm partner and university lecturer	25
4	E4	Male	Master's degree	Accounting	Internal audit manager in a large company	17
5	E5	Female	PhD	Information systems	Faculty member; digital transformation and data analytics specialist	16
6	E6	Male	PhD	Computer engineering / Artificial intelligence	Faculty member and intelligent systems consultant	15

7	E7	Male	Master's degree	Information technology	IT and enterprise systems development manager	14
8	E8	Female	Master's degree	Accounting / Auditing	Senior auditor at an audit firm	12
9	E9	Male	PhD	Information technology management	Researcher and consultant in business applications of AI	19
10	E10	Male	Master's degree	Accounting	Financial manager and head of internal audit	20
11	E11	Female	PhD	Accounting / Auditing	Faculty member and data-driven auditing specialist	14
12	E12	Male	Master's degree	Software engineering	Data analyst and intelligent solutions developer	11
13	E13	Male	PhD	Accounting	Faculty member and professional auditing consultant	23

The participants' characteristics indicate that the individuals selected possessed the qualifications necessary to provide expert perspectives on factors affecting dynamic interaction between auditors and artificial intelligence systems. The interview data are subsequently analyzed using the qualitative analytical method selected for the study, and the principal concepts, categories, and dimensions of the proposed model are extracted and explained.

After the semi-structured expert interviews had been conducted and transcribed, the data were analyzed using open coding. Interview transcripts were examined line by line, and meaningful statements concerning auditor–artificial intelligence interaction were converted into initial codes. Analysis proceeded without imposing predetermined frameworks, identifying topics such as the auditor's role and judgment, artificial intelligence capabilities and limitations, trust, algorithmic transparency, explainability, responsibility, human control, infrastructure, and ethical and legal requirements. Coding continued iteratively and recursively: similar codes were merged, ambiguous codes were refined, and new concepts were developed until saturation was reached. The findings indicated that effective interaction results from synergy among auditor professional judgment, data quality, algorithmic transparency, trust, human oversight, accountability, and organizational readiness. Artificial intelligence is effective in data analysis, anomaly detection, and risk assessment, but ultimate decision-making responsibility remains with the auditor.

After the initial codes had been extracted, the data were organized through axial coding to identify conceptual relationships among codes and categories. Following the paradigm approach, codes were classified into six dimensions: causal conditions, contextual conditions, intervening conditions, the core phenomenon, strategies, and consequences. The core phenomenon is dynamic interaction between auditors and artificial intelligence systems in the audit process, arising from the integration of human professional judgment and intelligent systems' analytical capabilities. The results identified technological pressures, information complexity, and the need to improve auditing as important causal factors, while strategies such as output control and risk management produce consequences including greater quality, trust, and value creation. Table 2 presents the axial coding results, including open codes and their corresponding principal categories.

Table 2. Axial Coding and Category Identification

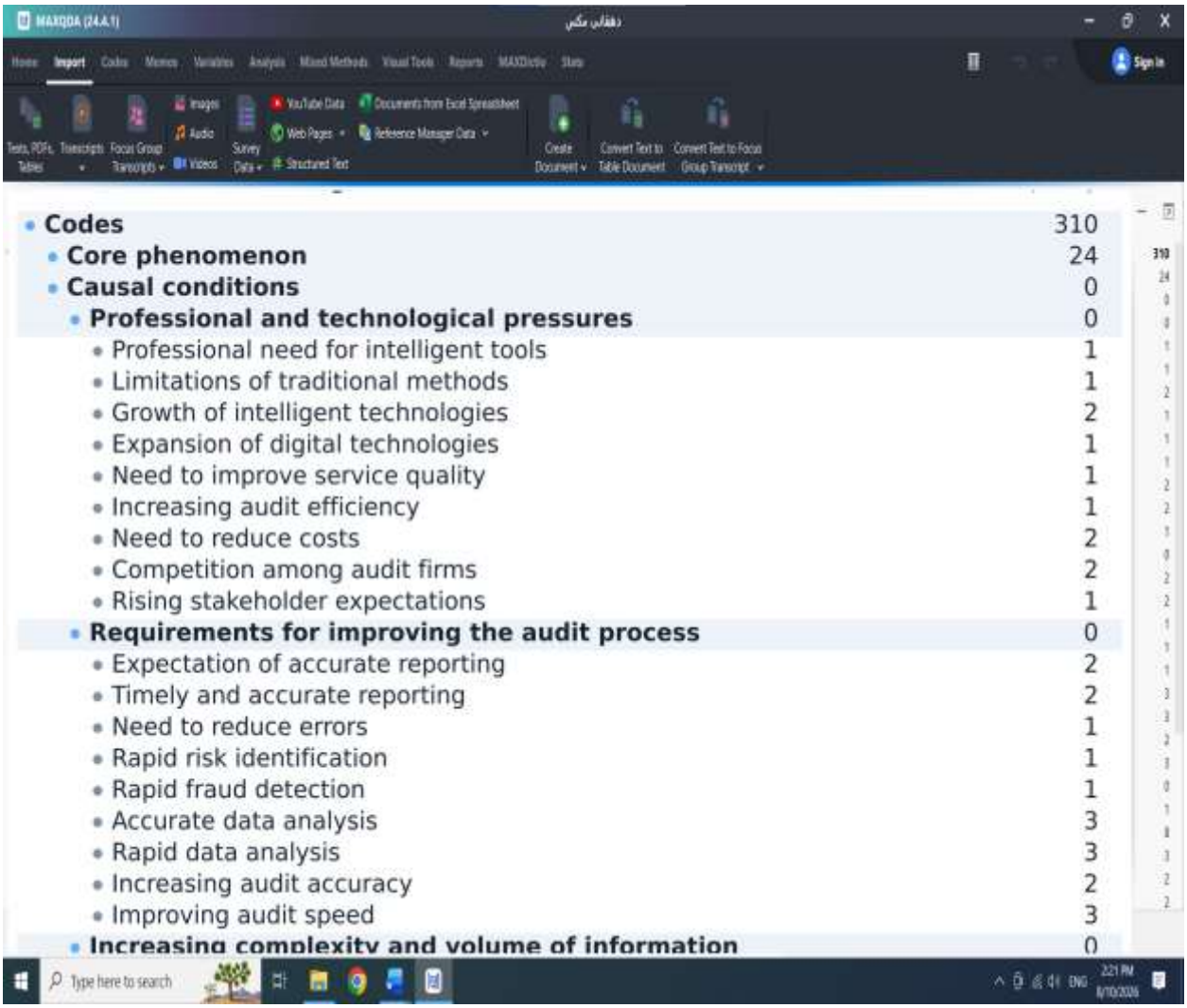
No.	Category (axial coding)	Open coding
1	Causal conditions	Professional and technological pressures
		Requirements for improving the audit process
		Increasing complexity and volume of information
2	Contextual conditions	Human capabilities and organizational cooperation

		Data and organizational readiness
		Technological infrastructure
3	Intervening conditions	Human and implementation barriers
		Technological and ethical risks
		Legal and professional barriers
4	Strategies	Control and validation of artificial intelligence outputs
		Intelligent risk and fraud management
		Intelligent audit data analysis
5	Consequences	Strengthening trust and value creation
		Improving performance and risk management
		Improving audit quality

Based on the analysis of open codes, causal conditions were classified into three principal categories: professional and technological pressures, requirements for improving the audit process, and increasing complexity and volume of information. Table 3 presents the principal categories and open codes associated with the causal conditions underlying dynamic interaction between auditors and artificial intelligence systems in the audit process.

Table 3. Principal Categories and Open Codes Associated with Causal Conditions

No.	Category (axial coding)	Open coding
1	Professional and technological pressures	Professional need for intelligent tools
		Limitations of traditional methods
		Growth of intelligent technologies
		Expansion of digital technologies
		Need to improve service quality
		Increasing audit efficiency
		Need to reduce costs
		Competition among audit firms
		Rising stakeholder expectations
2	Requirements for improving the audit process	Expectation of accurate reporting
		Timely and accurate reporting
		Need to reduce errors
		Rapid risk identification
		Rapid fraud detection
		Accurate data analysis
		Rapid data analysis
		Increasing audit accuracy
		Improving audit speed
3	Increasing complexity and volume of information	Fraud complexity
		Increasing volume of financial data
		Growth in financial transactions
		Complexity of economic activities
		Risk complexity
		Complexity of financial processes
		Complexity of the business environment
		Continuous system monitoring
		Complexity of accounting standards



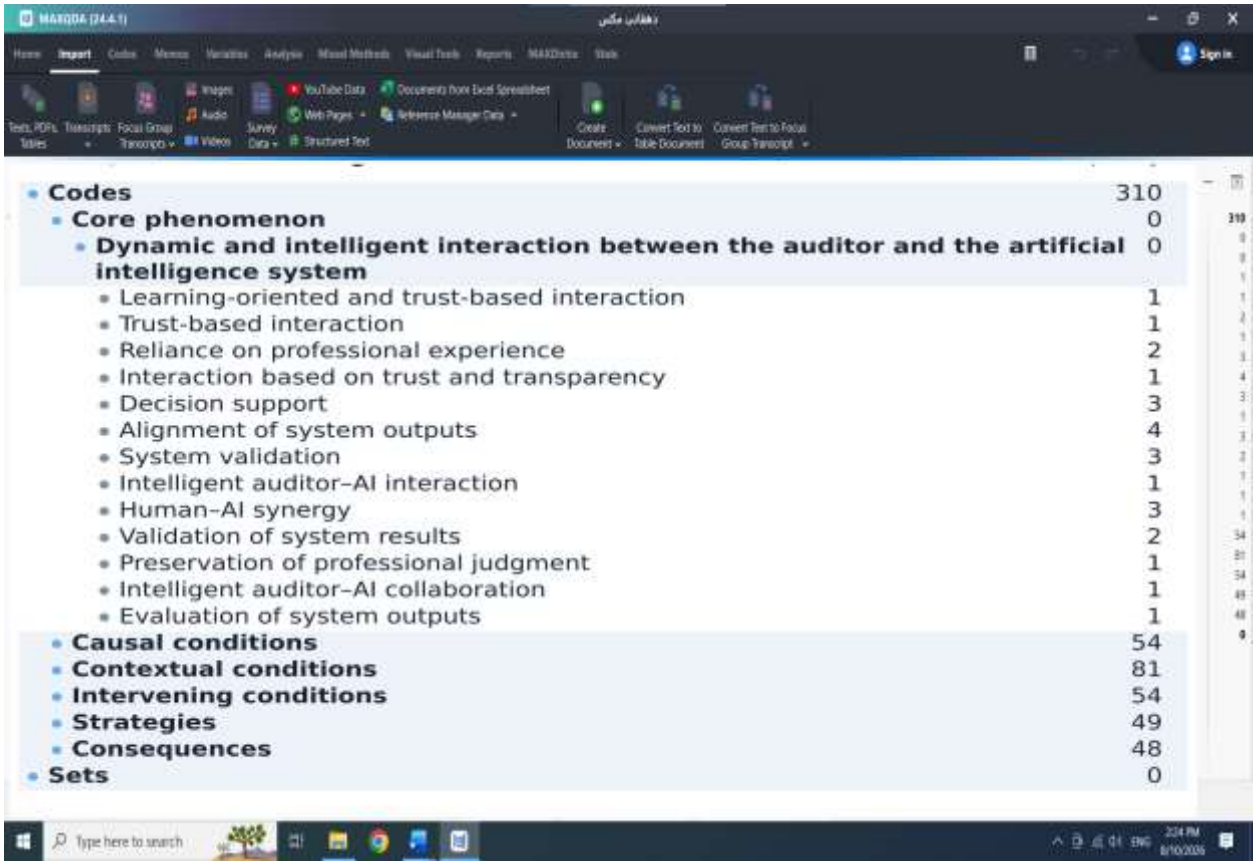
- **Increasing complexity and volume of information** 0
  - Fraud complexity 1
  - Increasing volume of financial data 8
  - Growth in financial transactions 3
  - Complexity of economic activities 2
  - Risk complexity 2
  - Complexity of financial processes 2
  - Complexity of the business environment 2
  - Continuous system monitoring 3
  - Complexity of accounting standards 1

In the study's paradigm model, the core phenomenon refers to the principal concept or process around which other categories develop and which organizes the relationships among causal conditions, contextual conditions, intervening factors, strategies, and consequences. Analysis of the expert interviews identified 'dynamic and intelligent interaction between the auditor and the artificial intelligence system' as the core phenomenon. This denotes a complementary, reciprocal, and evolving relationship between the auditor's human capabilities and the

processing, analytical, and learning capabilities of artificial intelligence systems across the audit process. Table 4 presents the principal category and extracted open codes associated with the study's core phenomenon.

Table 4. Principal Category and Extracted Open Codes Associated with the Core Phenomenon

No.	Category (axial coding)	Open coding
1	Dynamic and intelligent interaction between the auditor and the artificial intelligence system	Learning-oriented and trust-based interaction
		Trust-based interaction
		Reliance on professional experience
		Interaction based on trust and transparency
		Decision support
		Alignment of system outputs
		System validation
		Intelligent auditor–AI interaction
		Human–AI synergy
		Validation of system results
		Preservation of professional judgment
		Intelligent auditor–AI collaboration
		Evaluation of system outputs

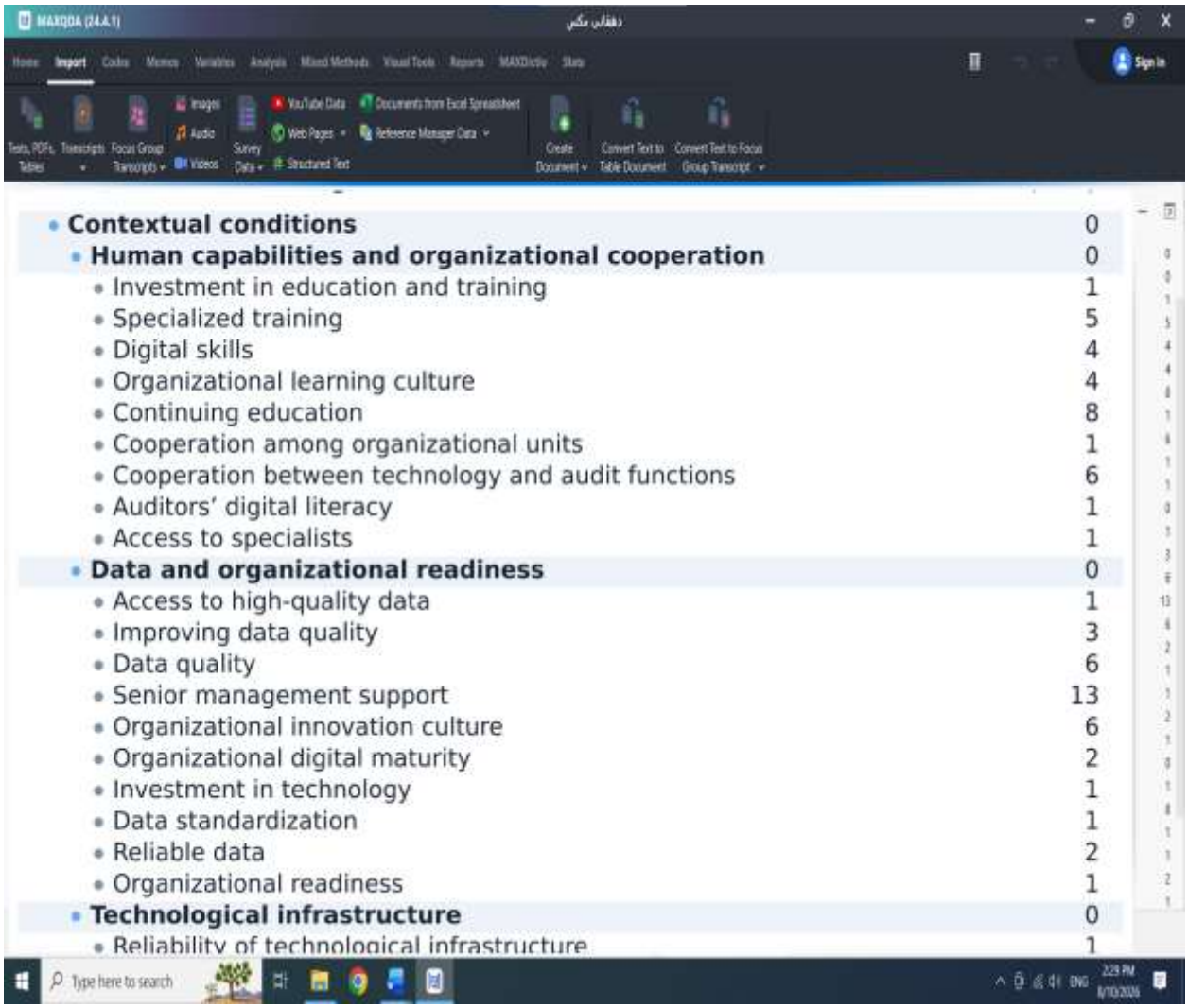


Contextual conditions refer to the intraorganizational and environmental settings, capacities, and resources that influence the emergence, implementation, and effectiveness of interaction between auditors and artificial intelligence systems. Although these conditions do not directly cause the core phenomenon, they provide the environment in which dynamic and intelligent interaction can occur, be strengthened, or be weakened. In other words, the presence of intelligent technology alone does not guarantee improvements in the audit process; its value

creation depends on workforce readiness, data quality, organizational support, and the adequacy of technological infrastructure. Table 5 presents the principal categories and open codes associated with the study's contextual conditions.

Table 5. Principal Categories and Open Codes Associated with Contextual Conditions

No.	Category (axial coding)	Open coding
1	Human capabilities and organizational cooperation	Investment in education and training
		Specialized training
		Digital skills
		Organizational learning culture
		Continuing education
		Cooperation among organizational units
		Cooperation between technology and audit functions
		Auditors' digital literacy
		Access to specialists
2	Data and organizational readiness	Access to high-quality data
		Improving data quality
		Data quality
		Senior management support
		Organizational innovation culture
		Organizational digital maturity
		Investment in technology
		Data standardization
		Reliable data
		Organizational readiness
3	Technological infrastructure	Reliability of technological infrastructure
		Information technology infrastructure
		Integration of information systems
		Access to intelligent software
		Software infrastructure
		Information infrastructure

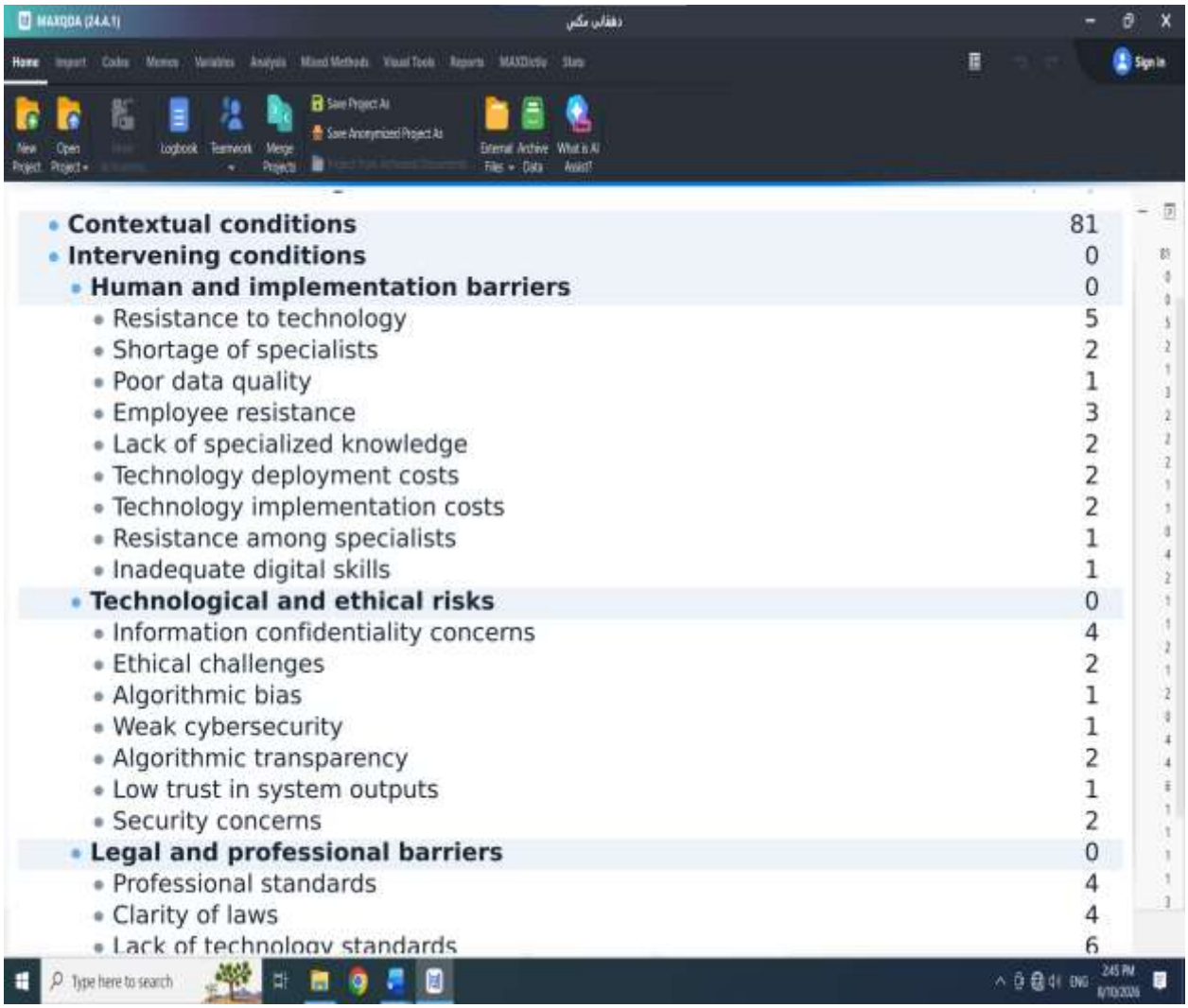


- **Technological infrastructure** 0
  - Reliability of technological infrastructure 1
  - Information technology infrastructure 8
  - Integration of information systems 1
  - Access to intelligent software 1
  - Software infrastructure 2
  - Information infrastructure 1

Intervening conditions refer to factors that can influence the magnitude, direction, and manner in which causal and contextual conditions affect the study's core phenomenon. These factors do not necessarily give rise to auditor–artificial intelligence interaction, but may facilitate or impede its implementation, acceptance, sustained use, and effectiveness. In this study, intervening conditions primarily emerged as human and implementation barriers, ethical and cultural considerations, and legal and professional constraints. Table 6 presents the principal categories and open codes associated with intervening conditions in the model of dynamic interaction between auditors and artificial intelligence systems.

Table 6. Principal Categories and Open Codes Associated with Intervening Conditions

No.	Category (axial coding)	Open coding
1	Human and implementation barriers	Resistance to technology
		Shortage of specialists
		Poor data quality
		Employee resistance
		Lack of specialized knowledge
		Technology deployment costs
		Technology implementation costs
		Resistance among specialists
		Inadequate digital skills
2	Human and cultural barriers	Information confidentiality concerns
		Ethical challenges
		Algorithmic bias
		Weak cybersecurity
		Algorithmic transparency
		Low trust in system outputs
		Security concerns
3	Legal and professional barriers	Professional standards
		Clarity of laws
		Lack of technology standards
		Ambiguity of legal liability
		Absence of specific regulations
		Lack of a legal framework
		Ambiguity of responsibility
		Formulation of regulations
		Legal ambiguity



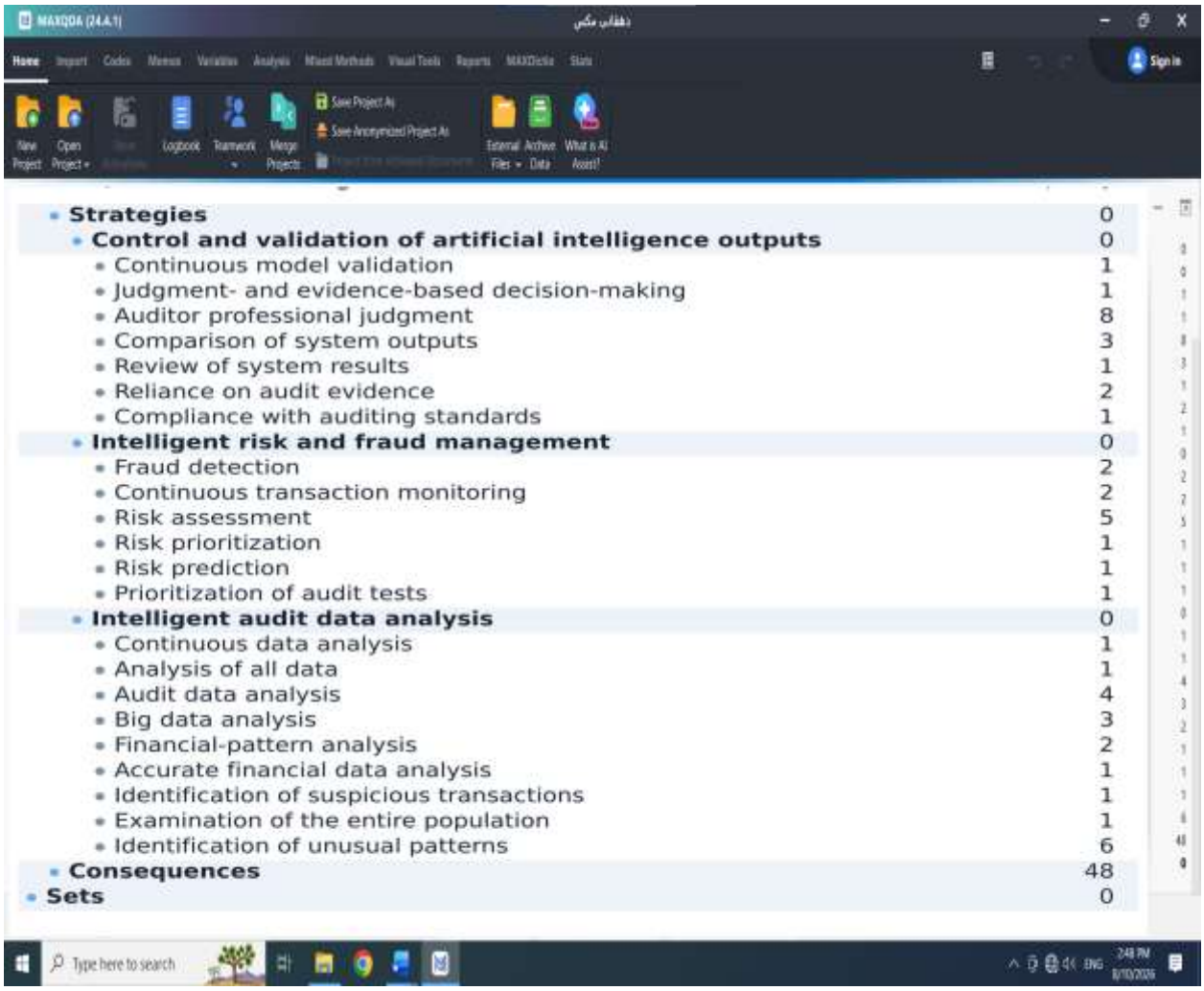
- **Legal and professional barriers** 0
  - Professional standards 4
  - Clarity of laws 4
  - Lack of technology standards 6
  - Ambiguity of legal liability 1
  - Absence of specific regulations 1
  - Lack of a legal framework 1
  - Ambiguity of responsibility 1
  - Formulation of regulations 3
  - Legal ambiguity 1

Strategies refer to deliberate actions, procedures, and mechanisms adopted by auditors, audit firms, and organizations in response to causal, contextual, and intervening conditions to establish effective, reliable, and responsible interaction between auditors and artificial intelligence systems. They describe how artificial intelligence capabilities are practically harnessed in the audit process so that benefits such as speed, accuracy, large-scale data analysis, and unusual-pattern detection are integrated with professional judgment, compliance with standards,

professional skepticism, and auditor responsibility. Table 7 presents the categories and open codes associated with strategies for dynamic interaction between auditors and artificial intelligence systems in the audit process.

Table 7. Categories and Open Codes Associated with Strategies

No.	Category (axial coding)	Open coding
1	Control and validation of artificial intelligence outputs	Continuous model validation
		Judgment- and evidence-based decision-making
		Auditor professional judgment
		Comparison of system outputs
		Review of system results
		Reliance on audit evidence
		Compliance with auditing standards
2	Intelligent risk and fraud management	Fraud detection
		Continuous transaction monitoring
		Risk assessment
		Risk prioritization
		Risk prediction
		Prioritization of audit tests
3	Intelligent audit data analysis	Continuous data analysis
		Analysis of all data
		Audit data analysis
		Big data analysis
		Financial-pattern analysis
		Accurate financial data analysis
		Identification of suspicious transactions
		Examination of the entire population
		Identification of unusual patterns

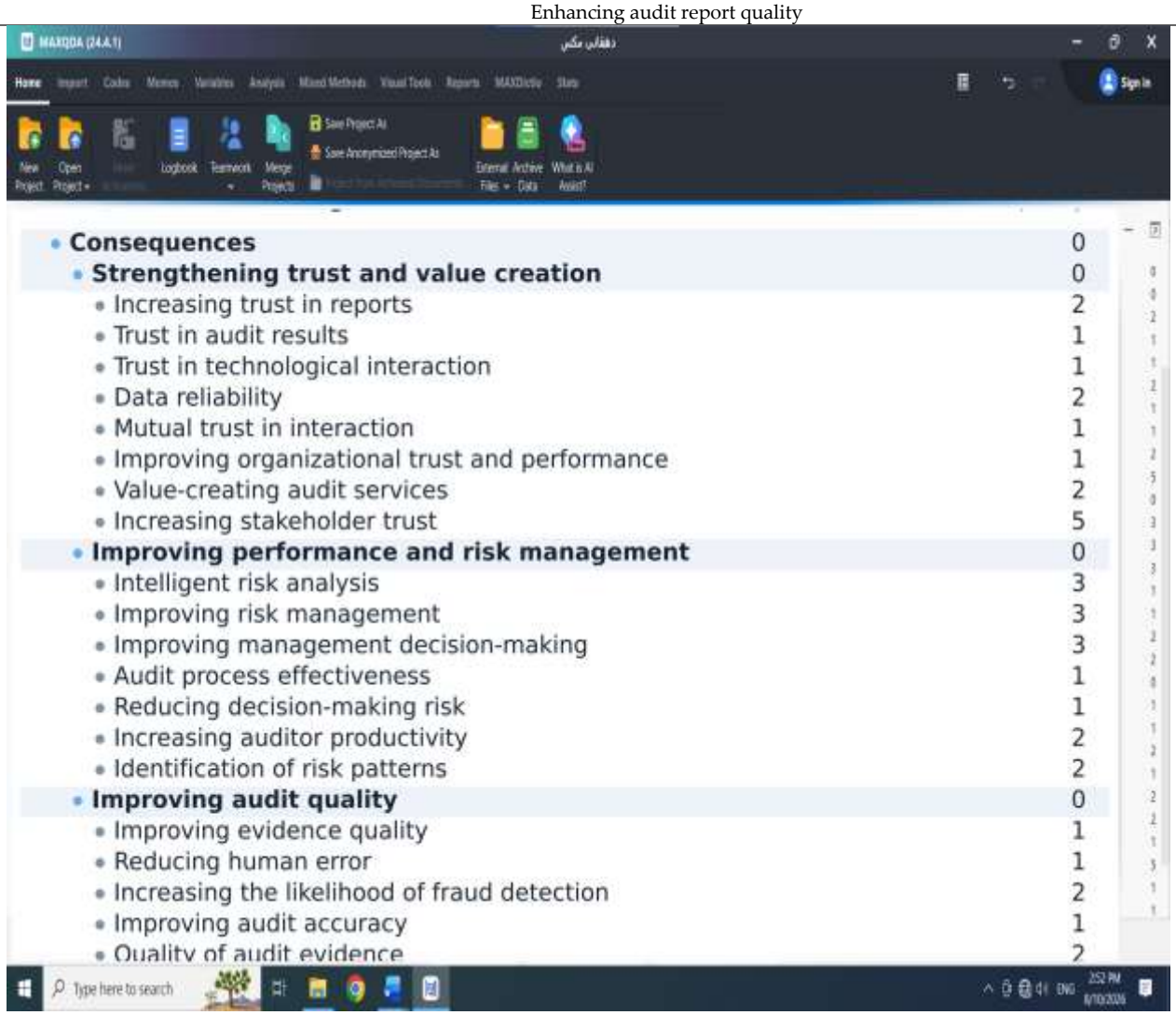


Consequences refer to the outcomes and achievements arising from dynamic and intelligent interaction between auditors and artificial intelligence systems when appropriate contextual conditions are present, intervening barriers are managed, and suitable strategies are implemented. When artificial intelligence's analytical and processing capabilities are combined with auditor professional judgment, professional skepticism, experience, and responsibility, the audit process is expected to improve in quality, speed, accuracy, data coverage, and informational value. Qualitative data analysis indicated that the consequences of this interaction can be explained through three principal categories: strengthening trust and value creation, improving performance and risk management, and improving audit quality. Table 8 presents the principal categories and open codes associated with the consequences of the model of dynamic interaction between auditors and artificial intelligence systems in the audit process.

Table 8. Principal Categories and Open Codes Associated with Consequences

No.	Category (axial coding)	Open coding
1	Strengthening trust and value creation	Increasing trust in reports
		Trust in audit results
		Trust in technological interaction
		Data reliability
		Mutual trust in interaction
		Improving organizational trust and performance

		Value-creating audit services
		Increasing stakeholder trust
2	Improving performance and risk management	Intelligent risk analysis
		Improving risk management
		Improving management decision-making
		Audit process effectiveness
		Reducing decision-making risk
		Increasing auditor productivity
		Identification of risk patterns
3	Improving audit quality	Improving evidence quality
		Reducing human error
		Increasing the likelihood of fraud detection
		Improving audit accuracy
		Quality of audit evidence
		Increasing audit speed
		Audit transparency
		Enhancing audit quality
		Improving audit performance
		Enhancing audit quality and reliability
		Enhancing audit report quality



• Improving audit quality	0
• Improving evidence quality	1
• Reducing human error	1
• Increasing the likelihood of fraud detection	2
• Improving audit accuracy	1
• Quality of audit evidence	2
• Increasing audit speed	2
• Audit transparency	1
• Enhancing audit quality	5
• Improving audit performance	1
• Enhancing audit quality and reliability	1
• Enhancing audit report quality	1

Selective coding is the third and final stage of qualitative data analysis under the grounded theory approach. At this stage, the researcher builds on open and axial coding to integrate, logically connect, and conceptually abstract the extracted categories into a comprehensive, coherent, explanatory theoretical framework. The fundamental objective of selective coding is to define the 'research storyline' and delineate systematic interaction among the model's dimensions through the paradigm model, comprising causal conditions, the core phenomenon, contextual conditions, intervening conditions, strategies, and consequences.

In this study, selective coding demonstrated that 'dynamic and intelligent interaction between the auditor and the artificial intelligence system' serves as the central core and core phenomenon. This is an interactive, adaptive, and reciprocal mechanism that emerges in response to environmental and technological drivers and is embedded in human, infrastructural, and organizational capabilities. Its effective realization requires specific strategies for data processing, risk management, and output evaluation, while implementation barriers, ethical challenges, and legislative gaps act as intervening variables affecting the quality and speed of the process. Ultimately, successful implementation of this model will deliver tangible gains in service quality, stakeholder trust, and professional audit performance.

Figure 1 presents the final model resulting from the qualitative phase of the study, depicting the causal, contextual, intervening, strategic, and consequential relationships of dynamic interaction between auditors and artificial intelligence systems within an integrated paradigm structure.

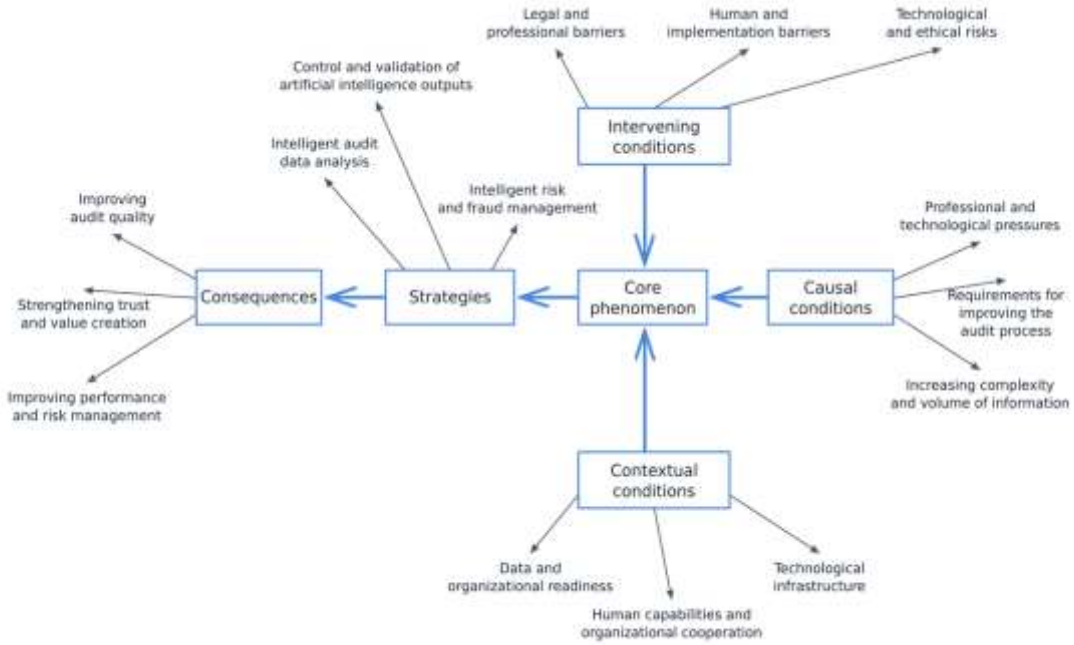


Figure 1. Paradigm Model of Dynamic Interaction

4. Discussion and Conclusion

The present study sought to develop a model of dynamic interaction between auditors and artificial intelligence systems in the audit process. The qualitative findings showed that the central phenomenon of the model is "dynamic and intelligent interaction between the auditor and the artificial intelligence system," understood as a reciprocal, adaptive, learning-oriented, and professionally controlled relationship between human judgment and machine analytical capabilities. The model further demonstrated that this central interaction develops under the influence of three groups of causal conditions—professional and technological pressures, requirements for improving the audit process, and increasing complexity and volume of information—while its effective realization depends on contextual conditions encompassing human capabilities and organizational cooperation, data and organizational readiness, and technological infrastructure. Human and implementation barriers, technological and ethical risks, and legal and professional barriers emerged as intervening conditions. In response to these conditions, three main strategies were identified: control and validation of AI outputs, intelligent risk and fraud management, and intelligent audit data analysis. Finally, the consequences were classified as strengthening trust and value creation, improving performance and risk management, and improving audit quality. Taken together, the results indicate that the value of AI in auditing does not originate merely from the technical sophistication of intelligent systems, but from the quality of interaction established between their analytical capabilities and auditors' professional judgment.

The first important finding concerns the nature of the core phenomenon itself. The results showed that auditor–AI interaction should not be regarded as a one-way relationship in which the auditor simply employs an intelligent technological instrument. Instead, it is a continuous process in which AI analyzes information, detects patterns and anomalies, generates recommendations, and assists risk identification, while the auditor interprets, evaluates, validates, modifies, or rejects those outputs using professional expertise, contextual understanding, and skepticism. The final paradigm model therefore portrays human and machine capabilities as complementary rather than

substitutive. This finding is consistent with the concept of the hybrid auditor proposed by Marina et al., according to which the future auditor integrates AI-based analytical capability with professional judgment and ethical accountability rather than surrendering professional decision-making to technology [6]. Similarly, Dang and To emphasize that AI-driven assurance represents a socio-technical transformation in which auditors and algorithmic systems operate within interconnected structures of judgment, accountability, and technological control [9]. Bostan likewise conceptualizes AI-enabled control and auditing through feedback mechanisms in which information flows between human and technological components and corrective actions continuously reshape system performance [10]. These converging perspectives explain why the present findings identified reciprocal learning, continuous validation, complementarity, and preservation of auditor responsibility as central principles of dynamic interaction.

The findings concerning causal conditions showed that growing professional and technological pressures, the need to improve audit procedures, and the increasing complexity and volume of financial information are major forces driving auditor–AI interaction. According to the interview data, traditional methods have become increasingly constrained by massive financial datasets, growth in digital transactions, complicated economic processes, evolving fraud techniques, stakeholder expectations, and demands for faster and more accurate reporting. This finding corresponds with Anwar and Akeel, who show that the integration of AI into audit workflows is driven by the need to process increasingly complex datasets, automate repetitive procedures, improve anomaly detection, and enhance audit efficiency [1]. Kassar and Jizi similarly identify AI and robotic process automation as important responses to growing demands for greater processing capacity, efficiency, and automation in accounting and auditing [24]. Fırat also argues that the growth of digital data and increasingly complex audit environments has transformed AI from a peripheral innovation into an increasingly relevant component of contemporary auditing [2]. In the Iranian context, Zanganeh et al. identified improved analytical capacity, faster processing, more accurate decision-making, and enhanced detection capabilities among the important opportunities associated with AI-based audit decision-making [28]. Thus, the present findings suggest that AI adoption is increasingly being shaped not simply by technological enthusiasm but by structural changes in the informational demands of auditing.

The second major finding concerns contextual conditions. The analysis demonstrated that possessing AI technologies alone cannot ensure effective auditor–system interaction. Human capabilities and organizational cooperation, data and organizational readiness, and appropriate technological infrastructure emerged as necessary enabling conditions. Specifically, specialized training, digital literacy, continuing education, cooperation between audit and information technology units, access to specialists, senior management support, reliable and standardized data, organizational digital maturity, investment in technology, and integrated information infrastructure were identified as crucial components. These findings strongly correspond with Karami and Haddadi, whose technology–organization–environment framework demonstrates that AI acceptance in auditing depends upon the simultaneous presence of technological, organizational, and environmental readiness [14]. Dastanpour Hosseinabadi et al. likewise identify organizational readiness, technological capability, professional competencies, and environmental conditions as important determinants of Industry 4.0 implementation in audit processes [18]. Sethia and Pandey further show that AI adoption in auditing evolves dynamically through interactions among organizational learning, technological investment, workforce readiness, perceived benefits, and institutional conditions [16]. Therefore, the present results reinforce the proposition that intelligent auditing requires organizational transformation rather than merely software acquisition.

Human competencies constitute an especially significant component of these contextual conditions. The results showed that auditors need digital literacy, data-analysis skills, familiarity with the capabilities and limitations of algorithms, and the ability to interact with technological specialists. This result is supported by Varma and Sharma, who emphasize that improvements in audit-team performance through AI depend on the manner in which technological resources are combined with human skills, coordination, and professional expertise [7]. Wei et al. likewise explain that organizations adopting generative AI-enabled intelligent auditing must develop dynamic capabilities allowing them to continually renew technological knowledge, routines, and human competencies [17]. Herlina et al. further demonstrate that the transformation of internal auditing through AI and electronic data processing requires changes in auditors' roles, technological competencies, and collaboration with information-processing functions [19]. Mehdizadeh and Saadati similarly identify specialized knowledge and professional preparedness among the central issues affecting the effective use of AI in tax auditing [22]. These findings imply that AI literacy should increasingly be considered part of the modern auditor's professional competency structure rather than a supplementary technical skill.

Another important contextual finding concerns data readiness. The study demonstrated that reliable interaction with intelligent systems is highly dependent on complete, accurate, standardized, timely, and trustworthy data. Senior management support, organizational innovation, investment in technology, and data standardization were also found to facilitate successful interaction. This result is consistent with Jamali et al., whose AI-based audit risk model for sustainability reporting underscores the importance of trustworthy data, technological readiness, and cybersecurity for effective intelligent auditing [27]. Hu et al. similarly show that continuous AI-based reporting, monitoring, and assurance depends fundamentally upon reliable data flows and integrated information architectures capable of supporting continuous analysis [3]. Ghorbani et al. also identify organizational and technological preparedness as significant components in acceptance of AI-based financial accounting systems [15]. The present findings therefore clarify that the accuracy of intelligent auditing cannot exceed the quality of the data and organizational infrastructure upon which algorithmic analyses are based.

The study also identified a broad range of intervening conditions capable of facilitating or restricting dynamic interaction. Human and implementation barriers included resistance to technology, shortages of specialists, inadequate digital skills, poor data quality, and implementation costs. Technological and ethical risks included information confidentiality concerns, algorithmic bias, weak cybersecurity, opacity, security concerns, and low trust in system outputs. Legal and professional barriers involved ambiguous responsibility, lack of specific regulations, insufficient technological standards, unclear legal liability, and gaps in professional frameworks. These findings correspond with Fırat, who identifies explainability, ethics, privacy, cybersecurity, skill deficiencies, and professional adaptation among the principal challenges of AI implementation in auditing [2]. Pérez-Calderón et al. likewise report that professionals recognize both the advantages of AI and challenges associated with implementation, competencies, data protection, and regulatory adaptation [25]. Baharom similarly emphasizes technological infrastructure, information security, competencies, ethical governance, and reliability as conditions affecting AI-supported internal audit effectiveness [21]. Mahmood et al. further show that cybersecurity threat intelligence is increasingly important in AI-driven internal audit risk assessment, highlighting the close relationship between intelligent auditing and information-security governance [20]. Thus, the findings demonstrate that the development of intelligent auditing creates new forms of risk that must themselves become objects of audit governance.

Trust and algorithmic transparency also emerged as important concerns. The study showed that effective interaction requires neither unquestioning reliance on AI outputs nor resistance to intelligent systems. Instead, trust should remain conditional and should be supported by evaluation, transparency, reliability, and professional validation. This interpretation is consistent with Ardhani et al., who found that auditors' trust in AI systems is shaped by perceived reliability, explainability, organizational arrangements, and professional experience [11]. Javidi et al. similarly emphasize trust as a fundamental component of AI-based auditing services and suggest that intelligent technologies generate professional and client value only where their outputs are perceived as credible and appropriately governed [12]. Sehat Barmcheh et al. further demonstrate that AI components involving intelligence, design, and choice can influence auditors' judgment, illustrating why auditors must retain an active evaluative role when interacting with intelligent decision-support systems [13]. Accordingly, the present findings support the notion of calibrated trust, in which auditors employ AI outputs as evidence-supporting inputs but preserve authority to question and override them.

Regarding strategies, the study identified control and validation of AI outputs as the first major response to the opportunities and risks of intelligent auditing. The extracted codes included continuous model validation, comparison and review of system outputs, reliance on audit evidence, professional judgment, and compliance with auditing standards. This finding supports the auditor-in-the-loop approach emphasized by Dang and To, in which human professional oversight remains an indispensable element of algorithmic assurance [9]. Marina et al. similarly stress that AI should augment rather than displace professional judgment and ethical accountability [6]. Gülten's examination of AI in independent auditing also supports maintaining professional responsibility and judgment when intelligent systems are incorporated into audit procedures [23]. Accordingly, validation functions as the mechanism through which computational outputs are transformed into professionally defensible audit evidence.

The second and third strategies were intelligent risk and fraud management and intelligent audit data analysis. These strategies included continuous transaction monitoring, fraud detection, risk assessment and prioritization, risk prediction, examination of entire data populations, big-data analysis, identification of suspicious transactions, and detection of unusual financial patterns. The findings are consistent with Wang et al., who demonstrate the potential of reinforcement-learning approaches for adaptive ESG audit decision-making and anomaly analysis [5]. Yadav et al. likewise illustrate the role of AI in continuous business-process verification and corporate auditing, supporting the transition from periodic auditing toward continuous monitoring [4]. Anwar and Akeel similarly identify anomaly detection, automation, large-scale data analysis, and risk-oriented decision support among the principal opportunities associated with integrating AI into audit workflows [1]. In addition, Barahoui Pirnia et al. demonstrate how emerging technologies, particularly AI and network analysis, may strengthen financial transparency and improve mechanisms for identifying relationships relevant to economic corruption [29]. These studies support the present finding that AI can broaden the scope of assurance from sample-based and retrospective procedures toward more comprehensive, continuous, and risk-responsive auditing.

Finally, the study identified three principal consequences of successful dynamic interaction: strengthening trust and value creation, improving performance and risk management, and improving audit quality. The model suggests that well-governed auditor–AI interaction can increase stakeholder confidence in audit reports, enhance evidence quality, reduce human error, increase the probability of fraud detection, improve audit speed and accuracy, strengthen risk management, and increase auditor productivity. These findings are aligned with Pérez-Calderón et al., who report that AI is perceived as capable of enhancing several dimensions of audit effectiveness and professional practice [25]. Nekoueimehr similarly reports relationships between AI use and auditing practices

in municipal environments, supporting the broader applicability of intelligent systems to different institutional audit settings [26]. Zanganeh et al. identify improved accuracy, analytical capacity, risk recognition, and decision support among the principal opportunities associated with AI-enabled audit decision-making [28]. The result is also compatible with the broader perspective of Barahoui Pirnia et al., in which integration of emerging technologies enhances transparency, oversight, and the informational value of auditing [29]. Overall, the model developed in the present study indicates that successful AI-enabled auditing is neither a process of technological replacement nor one of simple tool adoption. Rather, it is a hybrid professional system in which AI provides processing power, predictive capability, and pattern recognition while auditors retain interpretation, skepticism, ethical accountability, validation, and final responsibility. This conclusion is reflected directly in the study's final model, which rests on human–machine complementarity, continuous validation, reciprocal learning and feedback, and preservation of professional judgment.

The present study has several limitations that should be considered when interpreting its findings. First, because the research was qualitative and grounded in semi-structured interviews with a relatively small group of experts, the resulting model reflects analytically rich but context-dependent professional perceptions and cannot be statistically generalized to the entire population of auditors or audit organizations. Second, purposive and snowball sampling may have increased the likelihood that participants had relatively high levels of familiarity with technological transformation and artificial intelligence, potentially resulting in underrepresentation of auditors with lower technological readiness or more critical attitudes toward AI adoption. Third, the study focused primarily on the conceptual and professional dimensions of auditor–AI interaction rather than observing actual interaction behavior in live audit engagements. Consequently, discrepancies may exist between experts' descriptions of desirable interaction and the way auditors actually respond to intelligent systems under time pressure, client pressure, uncertainty, or organizational constraints. Fourth, rapid developments in generative AI, machine learning, explainable AI, cybersecurity, and audit regulation mean that some technological and institutional conditions identified in the model may change relatively quickly. Finally, differences among external auditing, internal auditing, governmental auditing, tax auditing, and specialized assurance engagements were not separately modeled, although the pattern and intensity of human–AI interaction may differ across these professional environments.

Future studies should quantitatively validate the proposed model using larger and more diverse samples of auditors and structural equation modeling so that the relationships among causal conditions, contextual factors, intervening conditions, strategies, and consequences can be statistically examined. Longitudinal research would also be useful for determining how auditor trust, technological competence, professional skepticism, and reliance on AI evolve as users accumulate practical experience with intelligent systems. Experimental studies could manipulate factors such as algorithmic explainability, system accuracy, risk level, task complexity, and management pressure to assess their effects on auditor reliance, automation bias, and professional judgment. Comparative studies across countries, regulatory systems, firm sizes, and audit types could determine whether the proposed model is stable across institutional contexts. Future investigations could also distinguish among specific AI technologies, including generative AI, machine learning, natural language processing, robotic process automation, and anomaly-detection systems, because different technologies may generate distinct patterns of interaction and professional risk. Additional research should examine how AI affects professional skepticism, responsibility attribution, auditor independence, documentation requirements, and the legal defensibility of audit judgments. Finally, field studies using actual audit engagements, system logs, behavioral observations, and

longitudinal performance data could provide stronger evidence about how human–AI collaboration affects audit quality in practice.

Audit firms, professional bodies, regulators, and organizations should approach AI implementation as an organizational and professional transformation rather than merely as a technological procurement decision. Audit firms should establish formal human-in-the-loop protocols specifying when AI outputs must be reviewed, how algorithmic recommendations should be validated against independent evidence, who has authority to override system recommendations, and how such decisions should be documented. Continuous professional development programs should integrate data analytics, algorithmic literacy, cybersecurity, AI ethics, and explainability with traditional competencies such as skepticism, evidence evaluation, and professional judgment. Organizations should also invest in data governance, standardization, information security, interoperable information systems, and reliable technological infrastructure before expanding AI-supported auditing. Senior management should encourage cooperation among audit, information technology, cybersecurity, data science, and legal functions so that technological and professional risks can be jointly managed. Audit firms should establish procedures for periodic validation of AI models, monitoring bias and performance drift, reviewing access controls and confidentiality protections, and maintaining traceable records of AI-supported decisions. Professional associations and regulators should additionally develop clearer standards concerning responsibility, documentation, algorithmic transparency, minimum validation requirements, and acceptable degrees of reliance on AI-generated evidence. These measures can help ensure that AI expands auditors' analytical capacity while preserving professional independence, accountability, skepticism, and responsibility for the final audit opinion.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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