

Developing a Comprehensive Model of AI-Based Audit Report Accuracy

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Abstract: This study aimed to develop and empirically validate a comprehensive model of artificial intelligence-based audit report accuracy by integrating technological, informational, human, organizational, governance, ethical, and professional determinants. An exploratory sequential mixed-methods design was employed in Tehran, Iran. In the qualitative phase, 18 experts in auditing, accounting, financial reporting, accounting information systems, and artificial intelligence were purposively selected and interviewed using semi-structured interviews until theoretical saturation was achieved. Qualitative data were analyzed through systematic coding and thematic categorization to identify the principal dimensions of AI-based audit report accuracy. In the quantitative phase, a researcher-developed questionnaire derived from the qualitative findings was administered to auditing, accounting, and financial professionals. Of 420 distributed questionnaires, 384 valid responses were retained for analysis. Reliability and validity of the measurement model were assessed using factor loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted, and the heterotrait-monotrait ratio. Partial least squares structural equation modeling with bootstrapping was used to test the proposed structural relationships. AI technological reliability ($\beta = 0.267$, $p < 0.001$), data quality and integrity ($\beta = 0.241$, $p < 0.001$), organizational readiness ($\beta = 0.156$, $p < 0.001$), explainability and transparency ($\beta = 0.121$, $p = 0.005$), AI governance and ethical-regulatory compliance ($\beta = 0.118$, $p = 0.007$), and information security and system controls ($\beta = 0.103$, $p = 0.012$) significantly predicted AI-assisted audit process quality. Auditor digital competence ($\beta = 0.286$, $p < 0.001$), AI governance ($\beta = 0.249$, $p < 0.001$), and explainability ($\beta = 0.203$, $p < 0.001$) significantly predicted human oversight and professional judgment. AI-assisted audit process quality ($\beta = 0.468$, $p < 0.001$) and human oversight ($\beta = 0.329$, $p < 0.001$) significantly predicted audit report accuracy. The interaction between these two factors was also significant ($\beta = 0.097$, $p = 0.015$). The final model explained 72.4% of the variance in audit report accuracy. Accurate AI-based audit reporting depends on the coordinated functioning of reliable technology, high-quality data, organizational readiness, governance safeguards, auditor digital competence, and sustained professional human oversight rather than on technological automation alone.

Keywords: Artificial intelligence; audit report accuracy; audit quality; professional judgment; human oversight; digital auditing; organizational readiness; AI governance.

1. Introduction

The rapid digital transformation of accounting and auditing has fundamentally altered the manner in which financial information is generated, processed, evaluated, and communicated to stakeholders. Among the technologies driving this transformation, artificial intelligence (AI) has assumed a particularly prominent position because of its capacity to process large volumes of structured and unstructured data, recognize complex patterns,

identify anomalies, automate repetitive procedures, and support professional decision-making. Traditional auditing has historically depended heavily on sampling, manual inspection, retrospective examination of accounting records, and professional judgment applied to a relatively limited set of available evidence. However, the growing volume, velocity, and complexity of organizational data have placed increasing pressure on conventional audit procedures and have intensified the need for technological mechanisms capable of expanding audit coverage while maintaining or improving the reliability of conclusions. AI-based systems offer the possibility of moving from periodic and sample-based auditing toward more continuous, data-intensive, and analytically sophisticated audit practices in which entire populations of transactions may be examined and unusual patterns may be identified more efficiently [1-3]. Accordingly, the integration of AI into auditing is no longer merely a technological innovation but represents a potentially important transformation in the architecture of audit evidence, audit judgment, and ultimately the accuracy of the audit report.

Audit report accuracy is particularly important because the audit report represents the principal formal mechanism through which auditors communicate their conclusions regarding financial statements and other audited information. Investors, creditors, managers, regulators, boards of directors, and other stakeholders rely on audit reports to reduce information asymmetry and to improve confidence in financial reporting. Any factor that improves the accuracy of the auditor's assessment can therefore contribute to the credibility of financial markets and organizational accountability, whereas errors in audit reporting may lead to inappropriate decisions, reduced trust, regulatory consequences, and substantial economic losses. In this context, AI has attracted increasing attention as a mechanism capable of improving audit quality through advanced data analysis, automated testing, anomaly detection, fraud-risk assessment, and enhanced identification of material misstatements. Evidence from recent research suggests that AI adoption can be positively associated with audit quality and integrated financial reporting, especially when intelligent technologies are effectively incorporated into audit processes and organizational reporting systems [4]. Similarly, empirical and review-based studies increasingly emphasize that AI can strengthen the quality, timeliness, and scope of accounting and auditing activities by extending auditors' analytical capabilities beyond the limitations of traditional procedures [5, 6].

One of the major expected advantages of AI in auditing is its ability to analyze substantially larger datasets than would normally be feasible through manual procedures. Machine learning algorithms can be trained to identify deviations from expected transaction patterns, unusual journal entries, suspicious relationships among accounts, and combinations of financial and operational indicators that may signal elevated audit risk. These capabilities are especially relevant in organizational environments characterized by high transaction volumes and interconnected digital systems. By expanding the range of evidence examined, AI can potentially reduce the risk that material anomalies remain undetected because of sampling limitations. Furthermore, intelligent systems may improve consistency by applying predefined analytical criteria across transactions and reporting periods, thereby reducing certain forms of random human error. The broader literature on the digital transformation of accounting indicates that AI is increasingly associated with automation, intelligent data processing, predictive analytics, and the transition toward digitally integrated accounting practices [7, 8]. In the auditing context, these developments create opportunities to transform the audit from a predominantly retrospective verification function into a more continuous and predictive process in which emerging risks can be identified earlier and incorporated into audit planning and reporting [2].

Nevertheless, the relationship between AI adoption and audit report accuracy cannot be understood solely in terms of technological sophistication. An AI system can generate reliable audit insights only to the extent that the

data supplied to it are accurate, complete, relevant, and appropriately structured. Inaccurate, incomplete, biased, or inconsistent input data can produce misleading outputs regardless of the computational power of the underlying algorithm. Thus, data quality and integrity constitute fundamental conditions for the effective use of AI in auditing. This issue becomes even more important when AI systems integrate information from multiple internal and external sources, because inconsistencies in data definitions, classification systems, or reporting standards may affect the reliability of automated conclusions. The integration of emerging technologies with financial reporting systems has therefore been discussed not only as a means of improving efficiency but also as a mechanism for enhancing transparency, traceability, and the reliability of financial information [9]. The same principle applies to audit reporting: unless auditors can establish confidence in the completeness and integrity of the information processed by intelligent systems, AI-generated analyses may increase technological complexity without necessarily improving the accuracy of the final report.

Algorithmic reliability represents another central concern. AI models may vary substantially in predictive accuracy, sensitivity to anomalies, generalizability across organizations, and vulnerability to model drift or inappropriate assumptions. Audit environments are also characterized by professional and contextual complexity that cannot always be captured completely through automated pattern recognition. A transaction that appears statistically unusual is not necessarily materially misstated, while a fraudulent transaction may be deliberately structured to resemble legitimate activity. Consequently, the usefulness of AI depends not only on its ability to identify patterns but also on whether its outputs can be meaningfully interpreted within an accounting and auditing framework. Recent reviews of AI and robotic process automation in accounting and auditing have emphasized that technological adoption can improve efficiency and analytical capacity while simultaneously introducing challenges related to implementation, professional competencies, organizational adaptation, and the interpretation of automated outputs [3, 10]. These concerns suggest that audit report accuracy is likely to emerge from an interaction between technological capability and the institutional and professional environment in which AI is deployed.

Explainability and transparency are particularly significant in this respect. Auditing is an evidence-based professional activity in which conclusions must be justified, documented, and capable of being reviewed. When an AI system produces a risk classification, identifies an anomalous transaction, or recommends additional audit procedures, the auditor must be able to understand sufficiently how the output was generated and why it should be considered relevant. Highly complex or opaque algorithms may generate technically accurate predictions while offering limited explanation of the reasoning underlying those predictions. This lack of transparency can create difficulties for audit documentation, review, accountability, and communication with regulators or clients. The ethical literature on AI in auditing has highlighted the importance of considering transparency, responsibility, independence, privacy, bias, and other ethical concerns alongside efficiency gains [11]. More recent studies have similarly noted that perceptions of ethical and operational risks can influence willingness to adopt AI within the audit function, indicating that technology adoption is shaped by confidence in the fairness, security, and accountability of intelligent systems [12]. Therefore, the accuracy of AI-assisted audit reports cannot be separated from the question of whether auditors can understand, challenge, and responsibly use AI-generated evidence.

Human expertise remains another indispensable component. Although AI can automate data processing and support the identification of high-risk areas, audit conclusions ultimately require professional judgment. Auditors must evaluate materiality, assess the sufficiency and appropriateness of audit evidence, interpret unusual findings, understand the business environment, consider management explanations, and determine whether identified

issues affect the audit opinion. The growing use of intelligent technologies therefore changes rather than eliminates the auditor's professional role. Evidence regarding the effects of AI-related training supports this interpretation. Training auditors to use AI has been associated with improvements in the timeliness of audit reporting, indicating that technological competence can influence the practical effectiveness of AI-enabled audit procedures [13]. Research has also suggested that auditor experience may moderate the relationship between the use of AI in auditing and financial reporting quality, implying that the benefits of technological adoption may depend partly on auditors' ability to combine machine-generated information with accumulated professional knowledge [14]. Thus, digital competence, professional skepticism, and human oversight should be treated as central elements in any comprehensive explanation of AI-based audit report accuracy.

The importance of professional judgment is further reinforced by research seeking to develop AI-based models of audit judgment. Such work reflects the increasing recognition that intelligent systems may assist auditors in complex decision environments but should be embedded within structured models that preserve professional accountability and critical evaluation [15]. The use of AI can support auditors by reducing cognitive workload, identifying patterns that may be difficult to detect manually, and directing attention toward areas of elevated risk. However, overreliance on automated recommendations can produce automation bias, particularly where users accept machine-generated outputs without sufficient independent evaluation. From the perspective of report accuracy, this creates a paradox: the same technology that can increase analytical precision may also introduce new sources of error if auditors lack the competence or willingness to critically assess automated findings. Consequently, human oversight should not be considered an external safeguard added after technological implementation; rather, it is an integral component of the AI-assisted audit process itself.

Organizational readiness is also essential because the effectiveness of AI depends on the broader infrastructure in which it operates. Successful adoption requires suitable information systems, access to high-quality digital data, technological investment, integration with existing audit workflows, senior management support, employee training, technical expertise, and mechanisms for updating and monitoring intelligent applications. Without these conditions, organizations may acquire AI technologies without obtaining meaningful improvements in audit quality. Empirical research on auditors' adoption of data analytics and AI demonstrates that acceptance of these technologies is influenced by multiple technological, organizational, and professional factors rather than by technical capability alone [16]. Similarly, studies examining AI in public-sector auditing suggest that intelligent systems may improve efficiency, transparency, control, and analytical capacity, but their benefits depend on appropriate institutional support and implementation mechanisms [17]. This indicates that a comprehensive model of audit report accuracy must account for organizational preparedness as an enabling condition through which AI capabilities can be translated into effective audit procedures.

Governance, ethical standards, and regulatory compliance constitute another important dimension. AI systems used in auditing process sensitive financial information and may influence decisions with significant legal and economic consequences. Appropriate governance is therefore required to determine responsibility for system design, validation, implementation, monitoring, and use. Auditors and firms must also address questions regarding confidentiality, cybersecurity, data ownership, model bias, privacy, professional independence, and accountability when AI-generated recommendations contribute to audit conclusions. Ethical challenges associated with AI auditing have been recognized for several years, particularly regarding the potential redistribution of decision-making authority between humans and intelligent systems [11]. More recent work has confirmed that perceived risks and ethical concerns can affect the adoption of AI-based audit technologies and may shape

practitioners' confidence in these systems [12]. This makes governance particularly relevant to report accuracy because poorly governed AI can create uncertainty regarding the reliability and defensibility of audit evidence even when the system performs efficiently from a computational perspective.

The potential influence of AI is also visible at the level of financial reporting behavior itself. Earlier research examining AI algorithms in relation to conservative financial reporting indicated that intelligent analytical techniques could contribute to stronger monitoring and more reliable reporting practices within listed companies [18]. As AI applications have developed, research has increasingly moved beyond isolated algorithmic functions toward broader questions of audit quality, integrated reporting, digital accounting, continuous auditing, and intelligent professional judgment [4, 7, 15]. This evolution in the literature suggests that AI is becoming embedded across multiple stages of the accounting-information cycle, from transaction processing and financial reporting to audit risk assessment and final assurance. Accordingly, the accuracy of the audit report is unlikely to be determined by any single AI capability. Instead, it is likely to reflect the cumulative functioning of data quality, algorithmic reliability, audit analytics, system controls, professional judgment, organizational infrastructure, and governance arrangements.

Current literature generally supports the proposition that AI can enhance accounting and auditing, although the emphasis of individual studies differs considerably. Some studies concentrate on technological applications and the transition toward digital or continuous auditing [2, 8]; others examine AI adoption and its implications for audit quality and reporting outcomes [4, 6]; while systematic reviews synthesize evidence regarding AI, robotic process automation, and the broader transformation of the accounting profession [1, 3, 10]. Other studies focus more specifically on professional readiness, audit judgment, training, experience, adoption determinants, or ethical risks [12-14, 16]. Collectively, these studies demonstrate that the effects of AI are multidimensional. At the same time, this fragmentation indicates an important conceptual limitation: technological, human, informational, organizational, ethical, and governance determinants are frequently examined separately, making it difficult to determine how they operate together to influence the accuracy of the final audit report.

Another limitation of the existing literature is that many studies discuss audit quality, efficiency, financial reporting quality, technology adoption, or digital transformation as broad outcomes, whereas the more specific concept of audit report accuracy receives comparatively less integrated attention. Audit quality and audit report accuracy are related but not identical constructs. A high-quality audit encompasses compliance with professional standards, adequate planning, sufficient evidence, independence, professional competence, documentation, and numerous process-related characteristics. Audit report accuracy, by contrast, refers more specifically to the correctness and evidential reliability of the conclusions communicated in the audit report. AI may improve some dimensions of audit quality without automatically ensuring accurate reporting. For example, automated testing may increase efficiency, but inaccurate data or poorly calibrated models may still produce misleading risk assessments. Similarly, AI may identify more anomalies while creating interpretive difficulties that weaken professional judgment. Therefore, a model specifically focused on audit report accuracy is needed to explain the conditions under which technological advantages ultimately translate into more reliable reporting outcomes.

This need is particularly relevant in emerging and developing professional environments where the adoption of AI may occur unevenly across audit firms and organizations. Differences in technological infrastructure, digital competencies, access to specialized training, regulatory development, organizational resources, and data management practices can affect the extent to which AI contributes to audit effectiveness. The transformation described in international research cannot therefore be assumed to occur identically in every national context.

Studies from different jurisdictions show growing interest in AI-based accounting and auditing, but they also reveal considerable variation in institutional readiness, adoption patterns, and professional concerns [5, 16, 19]. In Tehran, where audit firms, listed companies, financial institutions, regulatory organizations, and accounting professionals are highly concentrated, examination of these relationships is especially relevant because practitioners are increasingly exposed to digital reporting environments and emerging AI applications. Developing a contextually grounded model can therefore contribute both to theoretical clarification and to the practical management of AI adoption in the auditing profession.

The existing body of evidence consequently points toward a sociotechnical interpretation of AI-assisted auditing. From this perspective, accurate audit reporting results neither from human expertise alone nor from algorithmic performance alone. Instead, it arises from the interaction of technological reliability, high-quality and secure data, transparent analytical processes, professionally competent auditors, effective human oversight, organizational readiness, and robust ethical and regulatory governance. The systematic review literature increasingly supports such an integrative understanding by emphasizing that the transformation of accounting and auditing involves simultaneous changes in technology, work processes, professional roles, competencies, and organizational controls [1, 3]. Evidence regarding audit quality likewise indicates that successful AI implementation should be evaluated not simply by whether an organization has adopted AI but by whether its use produces meaningful improvements in assurance and reporting outcomes [6]. Therefore, the development of a comprehensive model can address an important gap by organizing previously dispersed determinants into a coherent structure and identifying the pathways through which AI-related capabilities and safeguards contribute to the accuracy of audit reports.

Accordingly, the aim of the present study was to develop and empirically validate a comprehensive model of AI-based audit report accuracy by integrating technological, informational, human, organizational, governance, ethical, and professional determinants among auditing and accounting experts and professionals in Tehran.

2. Methodology

This study employed an exploratory sequential mixed-methods design with the aim of developing and empirically validating a comprehensive model of artificial intelligence-based audit report accuracy. The research was applied in purpose and developmental-exploratory in nature, because it sought not only to identify the principal dimensions and determinants affecting the accuracy of audit reports generated or supported by artificial intelligence but also to integrate these determinants into a coherent conceptual and empirical model. The study was conducted in Tehran, Iran, due to the concentration of audit firms, accounting and auditing professionals, financial institutions, listed companies, universities, and specialists in emerging accounting technologies in the city. The research was implemented in two interconnected qualitative and quantitative phases. In the qualitative phase, the study population consisted of accounting and auditing experts, certified and experienced auditors, university faculty members specializing in accounting and auditing, financial reporting specialists, and experts familiar with artificial intelligence, accounting information systems, data analytics, and digital auditing. Participants were selected through purposive and criterion-based sampling to ensure that individuals possessed sufficient professional or academic knowledge concerning auditing, financial reporting, artificial intelligence applications, and the digital transformation of audit processes. Selection criteria included substantial professional or academic experience in accounting, auditing, financial management, accounting information systems, or artificial intelligence applications in financial decision-making; familiarity with audit reports and audit quality requirements; and willingness to participate in an in-depth expert interview. Sampling continued until theoretical saturation was

achieved, meaning that additional interviews no longer generated substantially new concepts, dimensions, or relationships relevant to the proposed model. Particular attention was given to achieving variation in participants' professional positions and areas of expertise so that the resulting framework would reflect technological, professional, organizational, and reporting perspectives rather than the views of a single occupational group.

The quantitative phase was designed to validate the conceptual framework derived from the qualitative findings and to examine the structural relationships among the identified dimensions of AI-based audit report accuracy. The statistical population in this phase consisted of auditors, senior auditors, audit supervisors and managers, accounting and financial professionals, internal auditors, financial managers, and accounting or auditing specialists working in audit firms, companies, financial organizations, and related professional institutions located in Tehran. Eligible respondents were required to have practical familiarity with auditing or financial reporting and sufficient awareness of digital accounting technologies, audit software, automated analytical procedures, or artificial intelligence applications. Participants were recruited using a purposive and accessible professional sampling strategy, with efforts made to include respondents from different organizational levels and professional backgrounds. The required quantitative sample size was determined according to the requirements of multivariate structural modeling and the complexity of the proposed measurement model. To ensure adequate statistical power and stable parameter estimation, the study aimed to obtain several hundred valid questionnaires, with the final sample retained after screening responses for completeness, response consistency, missing values, and abnormal response patterns. Participation in both phases was voluntary. Respondents were informed about the academic purpose of the research, the confidentiality of their information, the anonymous treatment of their responses, and their right to discontinue participation at any stage without consequence. The study procedures were designed in accordance with generally accepted ethical principles governing social science, accounting, and management research.

Data collection in the qualitative phase was conducted through semi-structured, in-depth expert interviews developed specifically for the objectives of the study. An interview protocol was prepared based on the conceptual domains of audit accuracy, audit quality, financial reporting reliability, artificial intelligence, automated decision-making, accounting information systems, professional judgment, technological infrastructure, data governance, and organizational control. The interview questions were deliberately open-ended to allow participants to explain how artificial intelligence could influence the accuracy of audit reports, what conditions could enhance or diminish such accuracy, what technological and professional risks were associated with AI-assisted auditing, and which organizational, human, regulatory, ethical, and data-related factors should be incorporated into a comprehensive model. Participants were also encouraged to identify relationships among the emerging factors and to explain mechanisms through which AI technologies might improve the detection of material misstatements, anomalies, inconsistencies, fraud indicators, or reporting errors. Follow-up and probing questions were used whenever necessary to clarify participants' statements, identify causal mechanisms, distinguish conceptually similar constructs, and obtain practical examples from the auditing environment. With participants' consent, interviews were recorded and subsequently transcribed for analysis. Interview notes were also maintained to record contextual information and analytical observations that could contribute to the interpretation of the transcripts.

The findings of the qualitative phase were subsequently used to develop a researcher-made questionnaire for the quantitative component of the study. Questionnaire items were generated directly from the categories, subcategories, and indicators identified through qualitative analysis and were refined with reference to the theoretical concepts underlying auditing, artificial intelligence adoption, information quality, professional

judgment, internal control, and audit reporting. The preliminary instrument was reviewed by a panel of specialists in accounting, auditing, research methodology, and information technology to evaluate the clarity, relevance, comprehensiveness, and conceptual appropriateness of each item. Content validity was assessed through expert judgment, and ambiguous, repetitive, or weakly related statements were revised or removed before distribution of the final questionnaire. The instrument was organized to measure the principal components of the proposed model, including the quality and integrity of financial and non-financial data used by AI systems, technological capability and algorithmic reliability, transparency and explainability of AI-generated results, information security and system controls, auditors' technological competence and professional expertise, professional skepticism and human oversight, organizational readiness for intelligent auditing, governance and internal control mechanisms, regulatory and ethical requirements, and the perceived accuracy and reliability of the final audit report. Depending on the conceptual framework emerging from the qualitative phase, additional dimensions concerning model bias, error detection capability, continuous auditing, automated risk assessment, integration of AI outputs with professional judgment, and the quality of audit evidence were also incorporated into the measurement instrument.

All questionnaire statements were assessed using a Likert-type response scale ranging from strong disagreement to strong agreement, allowing the degree of respondents' agreement with each proposed indicator to be quantified. Before the main administration, the questionnaire was pilot-tested among a small group of individuals with characteristics similar to those of the target population. The pilot phase was used to identify problems in item wording, comprehensibility, completion time, response variability, and preliminary reliability. Construct validity was subsequently assessed through measurement-model analysis, while internal consistency reliability was evaluated using Cronbach's alpha and composite reliability coefficients. Convergent validity was examined through factor loadings and average variance extracted, whereas discriminant validity was assessed by examining whether the proposed constructs were empirically distinguishable from one another. The combination of qualitative interviews and a quantitatively validated researcher-made questionnaire enabled the study to retain the contextual richness of expert knowledge while simultaneously testing whether the dimensions derived from that knowledge could be supported by empirical data from the broader professional population.

Data analysis was conducted separately for the qualitative and quantitative phases and was subsequently integrated to construct the final comprehensive model. In the qualitative phase, the interview transcripts were examined systematically through a coding and thematic categorization process. Analysis began with repeated reading of the transcripts to obtain familiarity with the data and identify meaningful statements concerning AI-supported auditing and audit report accuracy. Initial codes were assigned to statements representing important technological, professional, organizational, informational, ethical, regulatory, and reporting concepts. Conceptually similar codes were then compared and grouped into more abstract subcategories, and related subcategories were integrated into major categories representing the principal dimensions of the proposed model. Throughout the coding process, constant comparison was used to evaluate similarities and differences among participants' perspectives, refine category boundaries, eliminate conceptual redundancy, and identify relationships between antecedent conditions, facilitating mechanisms, control factors, and audit-report outcomes. Analytical attention was also directed toward identifying factors that could either strengthen or weaken the effect of artificial intelligence on audit report accuracy, such as poor-quality input data, algorithmic bias, insufficient system transparency, weak human supervision, lack of technological competence, inappropriate reliance on automated outputs, inadequate cybersecurity controls, and insufficient regulatory guidance. The qualitative analysis continued until a coherent conceptual structure was obtained and no substantial new dimensions emerged from

the data. The credibility of the qualitative findings was strengthened through expert review, comparison of interpretations across interviews, reconsideration of unclear codes, and verification of the logical consistency between raw statements, subcategories, major categories, and the final conceptual framework.

Quantitative data were analyzed using descriptive and inferential statistical procedures. Descriptive statistics were first calculated to summarize participants' demographic and professional characteristics as well as the distribution of responses to the study constructs. The dataset was screened for missing data, unusual response patterns, univariate and multivariate outliers, and the adequacy of item distributions before the structural analyses were conducted. The measurement properties of the research instrument were examined through confirmatory measurement-model procedures. Indicator reliability was assessed through standardized factor loadings, internal consistency was evaluated using Cronbach's alpha and composite reliability, and convergent validity was assessed using average variance extracted. Discriminant validity was evaluated through appropriate comparisons among latent constructs to ensure that theoretically distinct components of the model demonstrated sufficient empirical differentiation. After confirming the adequacy of the measurement model, structural equation modeling was employed to test the proposed relationships among the identified variables and to determine the relative contribution of the technological, informational, human, organizational, governance, ethical, and regulatory dimensions to AI-based audit report accuracy. Structural paths were evaluated according to their standardized coefficients, statistical significance, and explanatory power. The coefficient of determination for endogenous constructs was used to determine the proportion of variance explained by the model, while predictive relevance and effect-size indicators were considered to evaluate the practical importance of the proposed relationships.

Because the primary objective was model development and prediction across a relatively complex set of latent variables, partial least squares structural equation modeling was considered an appropriate analytical approach, particularly for simultaneously assessing the measurement and structural components of the proposed framework. Bootstrapping procedures were used to estimate the significance and stability of structural path coefficients without relying excessively on strict distributional assumptions. Collinearity among predictor constructs was also examined to ensure that structural estimates were not adversely affected by excessive overlap among explanatory variables. Direct and, where theoretically justified, indirect relationships were evaluated to determine whether factors such as organizational readiness, professional competence, AI governance, data quality, or human oversight operated as mechanisms through which technological capabilities influenced the accuracy of audit reports. The final model was established by integrating the empirical structural results with the qualitative findings, retaining constructs and relationships that demonstrated theoretical relevance, professional interpretability, and acceptable empirical support. This integration enabled the study to present a comprehensive model in which audit report accuracy was conceptualized not merely as a consequence of the technical performance of artificial intelligence algorithms, but as the outcome of an interconnected system involving data quality, technological reliability, auditor competence, professional judgment, organizational infrastructure, governance mechanisms, ethical safeguards, regulatory conditions, and appropriate human supervision of AI-assisted audit processes.

3. Findings and Results

The qualitative phase was completed with 18 experts from Tehran whose professional backgrounds covered external auditing, university-level accounting and auditing, financial reporting, accounting information systems, and artificial intelligence applications. The expert group consisted of 12 men (66.7%) and 6 women (33.3%), with a mean age of 45.8 years ($SD = 7.6$) and a mean professional or academic experience of 19.2 years ($SD = 6.4$). Ten

participants were practicing auditors, audit supervisors, or audit managers, five were university faculty members in accounting or auditing, and three were specialists in accounting information systems, data analytics, or artificial intelligence. Eleven experts held doctoral degrees, while the remaining seven held master's degrees or advanced professional qualifications in accounting and auditing. In the quantitative phase, 420 questionnaires were distributed among eligible accounting, auditing, and financial professionals in Tehran. Of these, 392 questionnaires were returned, and after excluding eight questionnaires because of excessive missing responses or evidently patterned responses, 384 questionnaires were retained for final analysis, corresponding to a usable response rate of 91.4%. Among the 384 participants, 282 (73.4%) were men and 102 (26.6%) were women. Participants had a mean age of 39.8 years ($SD = 8.9$) and an average of 13.6 years ($SD = 7.1$) of professional experience. In terms of age, 58 participants (15.1%) were younger than 30 years, 141 (36.7%) were between 30 and 39 years, 119 (31.0%) were between 40 and 49 years, and 66 (17.2%) were aged 50 years or older. Regarding educational attainment, 74 respondents (19.3%) held bachelor's degrees, 228 (59.4%) held master's degrees, and 82 (21.4%) held doctoral degrees or equivalent advanced professional qualifications. Professional experience was less than five years for 46 participants (12.0%), between five and ten years for 96 participants (25.0%), between 11 and 15 years for 103 participants (26.8%), between 16 and 20 years for 76 participants (19.8%), and more than 20 years for 63 participants (16.4%). With respect to professional position, 151 respondents (39.3%) were auditors or senior auditors, 92 (24.0%) were audit supervisors or managers, 85 (22.1%) were internal auditors, financial managers, or senior accounting professionals, and 56 (14.6%) were university faculty members, consultants, or specialists in accounting information systems and intelligent financial technologies. The diversity of participants in terms of professional role, education, and experience provided an appropriate empirical basis for evaluating a multidimensional model of artificial intelligence-based audit report accuracy.

Table 1. Qualitative Dimensions and Components of the Comprehensive Model of AI-Based Audit Report

Accuracy			
Main Dimension	Principal Components Identified in the Interviews	Representative Indicators	Experts Referring to Dimension, n (%)
Data Quality and Integrity	Data completeness, accuracy, consistency, timeliness, integration, and traceability	Reliable source data, elimination of duplicate records, standardized databases, validation of financial and non-financial inputs, audit trail completeness	18 (100.0)
AI Technological Reliability	Algorithmic accuracy, model robustness, anomaly detection capability, system stability, and adaptability	Low algorithmic error, accurate risk classification, detection of unusual transactions, stable model performance, continuous learning	17 (94.4)
Explainability and Transparency	Interpretability of AI outputs, traceability of decisions, transparency of model logic, and documentation	Explainable recommendations, accessible reasoning paths, documentation of model assumptions, ability to reproduce analytical results	15 (83.3)
Information Security and System Controls	Cybersecurity, access control, confidentiality, data protection, system authorization, and backup mechanisms	Controlled access, protection against unauthorized manipulation, secure data transfer, incident monitoring, system recovery mechanisms	14 (77.8)
Auditor Digital Competence	AI literacy, data analytics skills, technological self-efficacy, and ability to interpret machine-generated evidence	Understanding algorithmic outputs, data interpretation skills, familiarity with intelligent audit tools, ability to identify technological limitations	16 (88.9)
Human Oversight and Professional Judgment	Professional skepticism, critical review of AI outputs, auditor responsibility, and integration of machine results with expert judgment	Human validation, skepticism toward automated conclusions, override capability, contextual interpretation, final professional responsibility	18 (100.0)

Organizational Readiness	Technological infrastructure, management support, financial resources, organizational learning, and system integration	Adequate hardware and software, senior management commitment, training resources, integration with audit workflows, technical support	15 (83.3)
AI Governance and Ethical-Regulatory Compliance	Accountability, ethical AI use, regulatory conformity, bias control, privacy, and governance policies	Defined accountability, bias monitoring, ethical protocols, compliance with auditing standards, documentation of AI use	16 (88.9)
AI-Assisted Audit Process Quality	Audit coverage, risk assessment, evidence evaluation, continuous monitoring, and error or fraud detection	Wider transaction testing, real-time monitoring, enhanced risk prioritization, improved evidence analysis, identification of anomalies	17 (94.4)
Audit Report Accuracy	Correctness, reliability, consistency, material misstatement detection, and evidence-based reporting	Reduced reporting error, more accurate audit opinion, consistency with evidence, improved detection of material misstatement	18 (100.0)

The qualitative analysis resulted in ten central dimensions that collectively formed the conceptual foundation of the comprehensive model. Data quality and integrity and human oversight and professional judgment were mentioned by all 18 experts, indicating that participants did not consider artificial intelligence to be independently capable of ensuring accurate audit reporting. Rather, the experts consistently emphasized that the effectiveness of AI depends on the quality of the data entering the system and on the auditor's ability to critically evaluate, contextualize, and, when necessary, challenge machine-generated results. AI technological reliability and AI-assisted audit process quality were each emphasized by more than 94% of the experts, demonstrating the central role of algorithmic performance, anomaly detection, automated risk assessment, and broader audit coverage. Auditor digital competence and AI governance and ethical-regulatory compliance were also strongly represented, showing that technological implementation was perceived as inseparable from human capability and institutional accountability. Explainability and transparency were identified as particularly important because opaque algorithmic outputs could reduce auditors' ability to justify conclusions and could weaken the defensibility of the resulting audit opinion. Similarly, information security and system controls were viewed as necessary safeguards against unauthorized access, data manipulation, privacy breaches, and compromised analytical outputs. Organizational readiness emerged as a facilitating condition through which appropriate infrastructure, management commitment, technical support, and training could enable effective AI adoption. Overall, the qualitative findings demonstrated that audit report accuracy should be treated as the final outcome of an interconnected sociotechnical system rather than as a direct product of algorithmic sophistication alone. Based on these findings, data quality and integrity, AI technological reliability, explainability and transparency, information security and system controls, organizational readiness, and AI governance were conceptualized primarily as determinants of AI-assisted audit process quality, whereas auditor digital competence, explainability, and AI governance were also expected to reinforce human oversight and professional judgment. AI-assisted audit process quality and human oversight were subsequently specified as the two principal proximal determinants of audit report accuracy.

Table 2. Descriptive Statistics for the Constructs of the Proposed Model

Construct	No. of Items	Mean	SD	Skewness	Kurtosis	Observed Range
Data Quality and Integrity	5	4.06	0.61	-0.58	0.42	2.20–5.00
AI Technological Reliability	6	3.88	0.66	-0.43	0.18	2.00–5.00
Explainability and Transparency	5	3.62	0.71	-0.31	-0.12	1.80–5.00
Information Security and System Controls	4	3.79	0.68	-0.40	0.09	1.75–5.00
Auditor Digital Competence	5	3.74	0.70	-0.37	-0.08	1.80–5.00
Organizational Readiness	5	3.68	0.73	-0.34	-0.16	1.60–5.00

AI Governance and Ethical-Regulatory Compliance	6	3.84	0.67	-0.46	0.21	2.00–5.00
Human Oversight and Professional Judgment	5	4.10	0.59	-0.65	0.57	2.20–5.00
AI-Assisted Audit Process Quality	6	3.92	0.63	-0.49	0.28	2.00–5.00
Audit Report Accuracy	5	4.03	0.60	-0.61	0.48	2.20–5.00

As presented in Table 2, the mean scores for all constructs were above the theoretical midpoint of 3.00, suggesting that respondents generally evaluated the proposed technological, human, organizational, and governance conditions as important or relatively well established in relation to AI-assisted auditing. Human oversight and professional judgment obtained the highest mean score ($M = 4.10$, $SD = 0.59$), followed by data quality and integrity ($M = 4.06$, $SD = 0.61$) and audit report accuracy ($M = 4.03$, $SD = 0.60$). These results were consistent with the qualitative findings and indicated that respondents attached particular importance to continued professional responsibility and high-quality information inputs even when sophisticated artificial intelligence systems were employed. AI-assisted audit process quality also received a relatively high score ($M = 3.92$, $SD = 0.63$), suggesting generally favorable perceptions regarding the capacity of artificial intelligence to improve audit coverage, analytical procedures, risk assessment, and anomaly detection. In comparison, explainability and transparency had the lowest mean ($M = 3.62$, $SD = 0.71$), followed by organizational readiness ($M = 3.68$, $SD = 0.73$). These relatively lower values suggested that interpretability of intelligent systems and organizational preparedness represented comparatively greater challenges in the implementation of AI-assisted auditing. Auditor digital competence also remained lower than several technological and control-related dimensions ($M = 3.74$, $SD = 0.70$), indicating that development of human technological capability remains an important requirement for effective utilization of AI. The absolute skewness values ranged from 0.31 to 0.65 and the absolute kurtosis values ranged from 0.08 to 0.57. These values indicated no severe univariate distributional irregularities and confirmed that none of the constructs demonstrated problematic concentration at the upper or lower end of the scale. The observed score ranges additionally demonstrated adequate variability across respondents, supporting the suitability of the data for subsequent multivariate analysis.

Table 3. Measurement Model Reliability and Convergent Validity

Construct	Item Loading Range	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Data Quality and Integrity	0.78–0.87	0.884	0.889	0.915	0.683
AI Technological Reliability	0.76–0.88	0.901	0.906	0.925	0.674
Explainability and Transparency	0.77–0.85	0.872	0.878	0.908	0.665
Information Security and System Controls	0.79–0.86	0.846	0.852	0.897	0.686
Auditor Digital Competence	0.78–0.86	0.881	0.887	0.914	0.680
Organizational Readiness	0.76–0.85	0.866	0.871	0.904	0.653
AI Governance and Ethical-Regulatory Compliance	0.77–0.87	0.893	0.898	0.921	0.661
Human Oversight and Professional Judgment	0.81–0.89	0.905	0.909	0.929	0.724
AI-Assisted Audit Process Quality	0.80–0.89	0.914	0.919	0.934	0.703
Audit Report Accuracy	0.83–0.90	0.918	0.923	0.939	0.755

The results presented in Table 3 supported the reliability and convergent validity of the measurement model. All standardized indicator loadings exceeded 0.70, with the lowest loading being 0.76 and the highest being 0.90, indicating that the retained questionnaire items had strong relationships with their intended latent variables. Cronbach's alpha coefficients ranged from 0.846 for information security and system controls to 0.918 for audit report accuracy, and all values were therefore substantially above the conventional minimum criterion of 0.70. Similar findings were obtained for rho_A, which ranged from 0.852 to 0.923. Composite reliability coefficients

ranged from 0.897 to 0.939, confirming a high level of internal consistency without exceeding values that would indicate excessive item redundancy. Convergent validity was also satisfactory because the average variance extracted for every construct exceeded the recommended threshold of 0.50. AVE values ranged from 0.653 for organizational readiness to 0.755 for audit report accuracy, demonstrating that each latent construct explained considerably more than half of the variance in its corresponding observed indicators. Human oversight and professional judgment, AI-assisted audit process quality, and audit report accuracy demonstrated particularly strong convergent properties, with AVE values of 0.724, 0.703, and 0.755, respectively. Taken together, these results confirmed that the researcher-developed instrument reliably operationalized the qualitative dimensions identified during the first phase and provided an adequate measurement basis for evaluating the structural relationships proposed in the comprehensive model.

Table 4. Heterotrait-Monotrait Ratios for Assessment of Discriminant Validity

Construct	DQI	ATR	ET	ISSC	ADC	OR	GER	HOPJ	AAPQ	ARA
DQI	—									
ATR	0.62	—								
ET	0.51	0.64	—							
ISSC	0.48	0.56	0.58	—						
ADC	0.39	0.41	0.49	0.37	—					
OR	0.47	0.58	0.55	0.53	0.46	—				
GER	0.45	0.51	0.63	0.59	0.50	0.57	—			
HOPJ	0.42	0.46	0.61	0.44	0.67	0.49	0.64	—		
AAPQ	0.69	0.73	0.66	0.61	0.52	0.68	0.62	0.63	—	
ARA	0.63	0.67	0.62	0.57	0.59	0.61	0.66	0.75	0.81	—

Table 4 presents the heterotrait-monotrait ratio of correlations used to evaluate discriminant validity. All HTMT coefficients were below 0.85, ranging from 0.37 to 0.81, thereby indicating that the constructs were empirically distinguishable despite their theoretical interrelationships. The highest HTMT coefficient was observed between AI-assisted audit process quality and audit report accuracy (HTMT = 0.81), which was theoretically expected because improved audit process quality represents the most immediate technological and procedural antecedent of reporting accuracy. The association nonetheless remained below the conservative threshold of 0.85, supporting the distinction between the quality of the AI-supported audit process and the accuracy of the final audit report. Human oversight and professional judgment also demonstrated a relatively strong relationship with audit report accuracy (HTMT = 0.75), emphasizing the importance of professional review and auditor responsibility while retaining satisfactory discriminant validity. AI technological reliability was strongly but acceptably related to AI-assisted audit process quality (HTMT = 0.73), whereas data quality and integrity and organizational readiness showed corresponding HTMT values of 0.69 and 0.68 with AI-assisted audit process quality. Auditor digital competence was most strongly associated with human oversight and professional judgment (HTMT = 0.67), supporting the conceptual expectation that auditors with stronger technological knowledge are better able to critically evaluate and appropriately use algorithmic outputs. Similarly, AI governance and ethical-regulatory compliance showed meaningful associations with both human oversight (HTMT = 0.64) and audit report accuracy (HTMT = 0.66). Overall, no pair of constructs showed evidence of problematic conceptual overlap, confirming that the model represented a multidimensional structure in which technological reliability, data quality, transparency, security, professional capability, organizational preparedness, governance, audit process quality, professional oversight, and reporting accuracy constituted related but empirically distinct domains.

Table 5. Structural Model, Direct Effects, Indirect Effects, and Hypothesis Testing

Structural Relationship	β	t	p	95% Bootstrap CI	f ²	Result
Data Quality and Integrity → AI-Assisted Audit Process Quality	0.241	5.83	<0.001	0.158 to 0.322	0.094	Supported
AI Technological Reliability → AI-Assisted Audit Process Quality	0.267	6.19	<0.001	0.183 to 0.349	0.111	Supported
Explainability and Transparency → AI-Assisted Audit Process Quality	0.121	2.82	0.005	0.038 to 0.205	0.028	Supported
Information Security and System Controls → AI-Assisted Audit Process Quality	0.103	2.51	0.012	0.024 to 0.183	0.021	Supported
Organizational Readiness → AI-Assisted Audit Process Quality	0.156	3.62	<0.001	0.073 to 0.239	0.042	Supported
AI Governance and Ethical-Regulatory Compliance → AI-Assisted Audit Process Quality	0.118	2.71	0.007	0.034 to 0.201	0.025	Supported
Auditor Digital Competence → Human Oversight and Professional Judgment	0.286	6.74	<0.001	0.204 to 0.367	0.119	Supported
Explainability and Transparency → Human Oversight and Professional Judgment	0.203	4.89	<0.001	0.123 to 0.284	0.064	Supported
AI Governance and Ethical-Regulatory Compliance → Human Oversight and Professional Judgment	0.249	5.91	<0.001	0.167 to 0.330	0.087	Supported
AI-Assisted Audit Process Quality → Audit Report Accuracy	0.468	10.73	<0.001	0.383 to 0.551	0.312	Supported
Human Oversight and Professional Judgment → Audit Report Accuracy	0.329	7.48	<0.001	0.242 to 0.414	0.155	Supported
Data Quality and Integrity → Audit Report Accuracy	0.082	2.05	0.040	0.004 to 0.159	0.012	Supported
AI Governance and Ethical-Regulatory Compliance → Audit Report Accuracy	0.074	1.98	0.048	0.002 to 0.147	0.010	Supported
AI-Assisted Audit Process Quality × Human Oversight → Audit Report Accuracy	0.097	2.44	0.015	0.021 to 0.175	0.018	Supported
Data Quality and Integrity → Audit Process Quality → Audit Report Accuracy	0.113	4.98	<0.001	0.071 to 0.160	—	Significant indirect effect
AI Technological Reliability → Audit Process Quality → Audit Report Accuracy	0.125	5.31	<0.001	0.082 to 0.174	—	Significant indirect effect
Explainability and Transparency → Audit Process Quality → Audit Report Accuracy	0.057	2.69	0.007	0.018 to 0.100	—	Significant indirect effect
Information Security and System Controls → Audit Process Quality → Audit Report Accuracy	0.048	2.35	0.019	0.011 to 0.089	—	Significant indirect effect
Organizational Readiness → Audit Process Quality → Audit Report Accuracy	0.073	3.39	0.001	0.034 to 0.119	—	Significant indirect effect
AI Governance → Audit Process Quality → Audit Report Accuracy	0.055	2.60	0.009	0.017 to 0.099	—	Significant indirect effect
Auditor Digital Competence → Human Oversight → Audit Report Accuracy	0.094	4.90	<0.001	0.060 to 0.136	—	Significant indirect effect
Explainability and Transparency → Human Oversight → Audit Report Accuracy	0.067	4.03	<0.001	0.037 to 0.104	—	Significant indirect effect
AI Governance → Human Oversight → Audit Report Accuracy	0.082	4.56	<0.001	0.049 to 0.121	—	Significant indirect effect

The structural model results presented in Table 5 provided substantial empirical support for the proposed comprehensive model. Among the antecedents of AI-assisted audit process quality, AI technological reliability demonstrated the strongest standardized effect ($\beta = 0.267$, $t = 6.19$, $p < 0.001$), followed by data quality and integrity ($\beta = 0.241$, $t = 5.83$, $p < 0.001$). These findings indicated that the capacity of AI to improve the audit process depends primarily on the reliability of algorithms and the quality of the information on which those algorithms operate. Organizational readiness also exerted a significant positive effect on AI-assisted audit process quality ($\beta = 0.156$, $p < 0.001$), confirming that infrastructure, management commitment, workflow integration, technical support, and

organizational learning substantially facilitate the effective use of intelligent auditing systems. Explainability and transparency ($\beta = 0.121$, $p = 0.005$), AI governance and ethical-regulatory compliance ($\beta = 0.118$, $p = 0.007$), and information security and system controls ($\beta = 0.103$, $p = 0.012$) also demonstrated statistically significant positive effects, although their individual effect sizes were smaller. The second part of the model showed that auditor digital competence was the strongest predictor of human oversight and professional judgment ($\beta = 0.286$, $p < 0.001$), followed by AI governance and ethical-regulatory compliance ($\beta = 0.249$, $p < 0.001$) and explainability and transparency ($\beta = 0.203$, $p < 0.001$). These relationships indicated that effective human oversight requires not only professional auditing knowledge but also sufficient technological capability, transparent AI outputs, and organizationally established accountability mechanisms. In predicting the final outcome, AI-assisted audit process quality had the largest direct effect on audit report accuracy ($\beta = 0.468$, $t = 10.73$, $p < 0.001$; $f^2 = 0.312$), representing a moderate-to-large substantive effect. Human oversight and professional judgment also had a strong positive effect on report accuracy ($\beta = 0.329$, $t = 7.48$, $p < 0.001$; $f^2 = 0.155$), showing that enhanced algorithmic capabilities do not eliminate the contribution of auditor judgment. Data quality and integrity ($\beta = 0.082$, $p = 0.040$) and governance and ethical-regulatory compliance ($\beta = 0.074$, $p = 0.048$) maintained smaller but significant direct effects on report accuracy after the two principal mediating mechanisms were included. Furthermore, the interaction between AI-assisted audit process quality and human oversight was significant ($\beta = 0.097$, $p = 0.015$), demonstrating that the positive effect of an AI-enhanced audit process on reporting accuracy became stronger when the level of professional human oversight was high. The mediation analysis reinforced this interpretation. AI technological reliability showed the strongest indirect technological effect on report accuracy through audit process quality ($\beta = 0.125$, $p < 0.001$), followed by data quality and integrity ($\beta = 0.113$, $p < 0.001$). Auditor digital competence also significantly influenced report accuracy through human oversight and professional judgment ($\beta = 0.094$, $p < 0.001$). Significant indirect effects were further observed for explainability, security controls, organizational readiness, and AI governance. The explanatory power of the model was substantial. The antecedent variables explained 64.2% of the variance in AI-assisted audit process quality ($R^2 = 0.642$; adjusted $R^2 = 0.636$), while auditor digital competence, explainability, and AI governance explained 53.7% of the variance in human oversight and professional judgment ($R^2 = 0.537$; adjusted $R^2 = 0.533$). Most importantly, the complete model explained 72.4% of the variance in audit report accuracy ($R^2 = 0.724$; adjusted $R^2 = 0.719$), indicating strong explanatory capacity for a behavioral and organizational accounting model. Predictive relevance values were also positive for AI-assisted audit process quality ($Q^2 = 0.438$), human oversight and professional judgment ($Q^2 = 0.361$), and audit report accuracy ($Q^2 = 0.523$), demonstrating satisfactory out-of-sample predictive relevance. Collinearity assessment produced inner VIF values ranging from 1.28 to 2.74, all substantially below conservative problematic thresholds, indicating that the structural coefficients were not materially distorted by multicollinearity. The standardized root mean square residual was 0.061, the normed fit index was 0.912, and RMS_theta was 0.109, collectively supporting the overall adequacy of the estimated model.

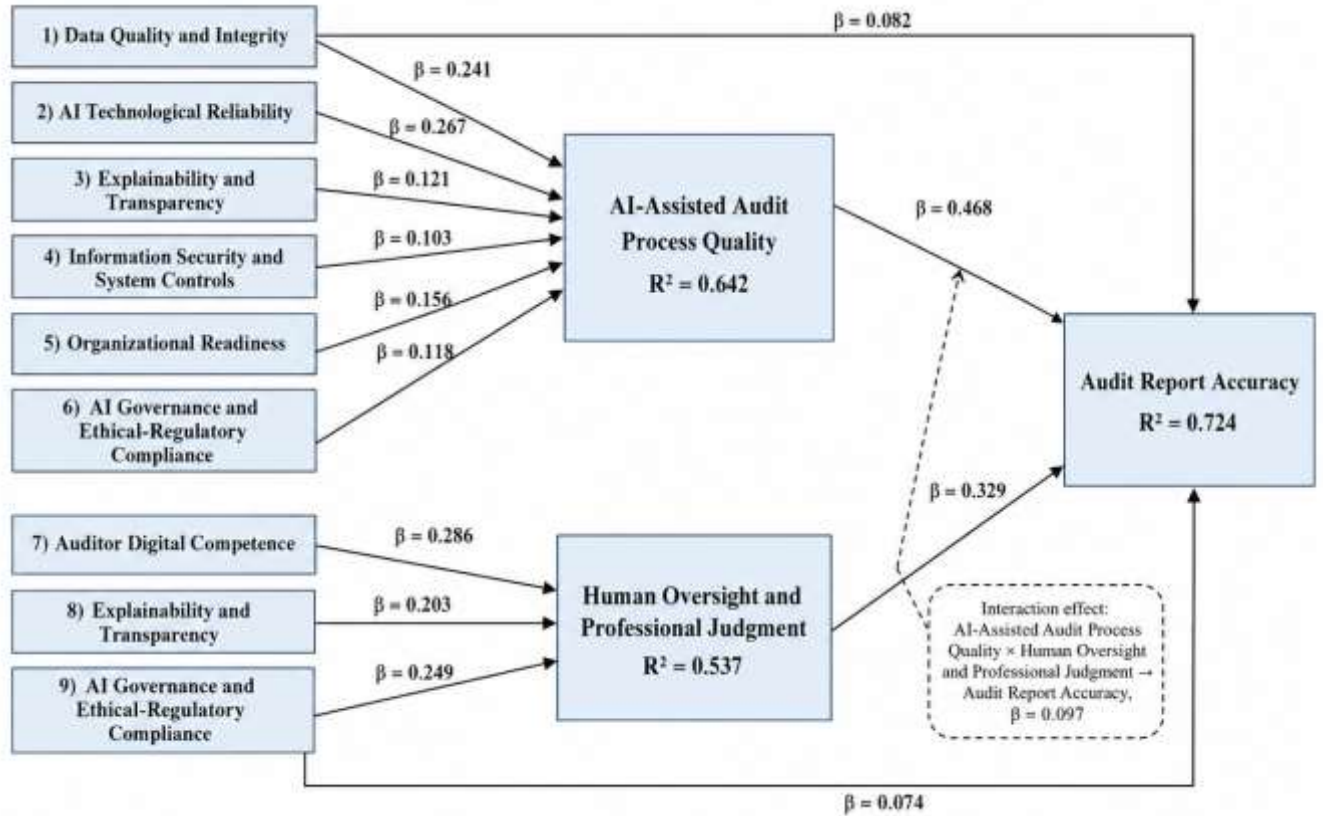


Figure 1. Final Comprehensive Structural Model of AI-Based Audit Report Accuracy

The final structural model demonstrated that AI-based audit report accuracy emerged through two complementary pathways rather than through a purely technological mechanism. The first pathway was an AI-assisted audit process pathway in which data quality and integrity, technological reliability, explainability, information security and system controls, organizational readiness, and AI governance jointly enhanced the quality of AI-supported audit procedures, which in turn produced a strong improvement in audit report accuracy. The second pathway was a human professional control pathway in which auditor digital competence, explainability, and governance strengthened human oversight and professional judgment, which subsequently increased report accuracy. The significant interaction between AI-assisted audit process quality and human oversight additionally demonstrated complementarity between artificial and human intelligence. In other words, superior technological performance produced its greatest contribution to reporting accuracy when auditors maintained active professional skepticism, evaluated the plausibility of machine-generated evidence, interpreted results within the economic and organizational context of the audited entity, and retained responsibility for the ultimate audit conclusion. The final model therefore did not support a substitution perspective in which artificial intelligence replaces the professional auditor. Instead, it supported an augmentation perspective in which high-quality data, reliable algorithms, secure and transparent systems, digitally competent auditors, appropriate organizational infrastructure, strong governance, and continuous human supervision operate as mutually reinforcing components. The substantial explained variance in audit report accuracy further indicated that the comprehensive model captured a large proportion of the technological, human, organizational, and governance conditions underlying accurate AI-assisted audit reporting. Accordingly, the final model conceptualized audit report accuracy as the product of coordinated interaction among information quality, algorithmic capability, institutional readiness, governance safeguards, professional competence, and accountable human judgment.

4. Discussion and Conclusion

The present study developed and empirically evaluated a comprehensive model of artificial intelligence-based audit report accuracy by integrating technological, informational, human, organizational, governance, ethical, and professional dimensions. The findings indicated that audit report accuracy in an AI-enabled environment cannot be explained by the presence of artificial intelligence technology alone. Rather, accuracy emerged from a multidimensional system in which data quality and integrity, AI technological reliability, explainability and transparency, information security and system controls, organizational readiness, AI governance and ethical-regulatory compliance, auditor digital competence, human oversight and professional judgment, and AI-assisted audit process quality operated jointly. The final structural model explained 72.4% of the variance in audit report accuracy, demonstrating considerable explanatory power. Among the proximal predictors, AI-assisted audit process quality had the strongest direct effect on audit report accuracy ($\beta = 0.468$), followed by human oversight and professional judgment ($\beta = 0.329$). In addition, the interaction between AI-assisted audit process quality and human oversight was significant ($\beta = 0.097$), indicating that the contribution of AI-enhanced audit procedures to report accuracy was stronger when professional human control and judgment were also strong. These findings support an augmentation perspective in which artificial intelligence improves audit performance most effectively when embedded within a professionally governed auditing system rather than operating as a substitute for the auditor.

The strong effect of AI-assisted audit process quality on audit report accuracy represents one of the most important findings of the study. The result suggests that AI contributes to report accuracy principally by improving the quality of underlying audit procedures, including risk assessment, analytical review, anomaly detection, transaction examination, evidence evaluation, and continuous monitoring. This interpretation is consistent with studies describing AI as a mechanism for transforming auditing from sample-based and retrospective procedures toward more comprehensive, continuous, and data-intensive assurance practices [1, 2]. AI and machine-learning technologies provide auditors with the ability to examine large quantities of financial information, identify unusual patterns, and prioritize high-risk transactions more efficiently than conventional manual procedures [5]. The finding also corresponds with evidence showing that AI adoption is associated with improvements in audit quality and integrated financial reporting [4]. Similarly, reviews of the empirical literature have concluded that AI can contribute to audit quality by increasing analytical capacity, improving fraud and error detection, and enhancing the consistency and timeliness of audit work [6]. The present findings extend this literature by indicating that improvements in audit process quality constitute a central mechanism through which these technological capabilities are translated into greater accuracy of the final audit report.

AI technological reliability was the strongest antecedent of AI-assisted audit process quality ($\beta = 0.267$). This finding indicates that the usefulness of AI depends heavily on the accuracy, robustness, stability, and analytical capability of the underlying technological system. An AI tool that produces inconsistent classifications, fails to identify relevant anomalies, or responds unpredictably to changing data patterns cannot meaningfully strengthen the audit process regardless of its level of automation. This result is compatible with the broader literature emphasizing machine learning, intelligent data processing, robotic process automation, and advanced analytical systems as central components of contemporary auditing transformation [3, 8]. The transition from traditional accounting and auditing toward digital systems similarly requires reliable technological architectures capable of integrating data and generating decision-relevant outputs [7]. The finding also aligns with the work of Kindzeka,

who highlighted the potential of AI to reshape accounting, auditing, and financial reporting through automation and improved analytical capability [19]. Accordingly, the technological dimension of the proposed model is not merely concerned with whether AI exists within an audit organization, but with whether it performs with sufficient reliability to produce evidence that can legitimately influence professional conclusions.

Data quality and integrity emerged as the second strongest predictor of AI-assisted audit process quality ($\beta = 0.241$) and also retained a small but statistically significant direct effect on audit report accuracy ($\beta = 0.082$). This finding is theoretically important because AI systems are inherently dependent on their input data. Even sophisticated algorithms may generate inaccurate outputs when financial and non-financial data are incomplete, duplicated, outdated, inconsistent, or improperly classified. Therefore, technological intelligence cannot compensate fully for weak informational foundations. The importance of integrated, transparent, and trustworthy financial data has also been emphasized in frameworks linking AI with other digital technologies such as blockchain to enhance financial reporting and auditing [9]. Furthermore, research concerning AI algorithms and conservative financial reporting suggests that intelligent analysis can support more reliable financial reporting when it operates on appropriate accounting information [18]. The present finding therefore reinforces the principle that the quality of AI-supported auditing begins with the quality of the data environment. In practical terms, organizations seeking to improve audit report accuracy through AI must first ensure that their databases, accounting systems, transaction records, and information governance mechanisms provide reliable and traceable data suitable for intelligent analysis.

Organizational readiness also exerted a significant positive effect on AI-assisted audit process quality ($\beta = 0.156$). This result demonstrates that AI implementation is an organizational transformation rather than a purely technical installation. Management support, digital infrastructure, integration of AI with existing audit procedures, technical resources, staff training, and organizational learning all determine whether the potential capabilities of AI are translated into actual improvements in auditing. This result is consistent with evidence showing that audit professionals' adoption of data analytics and artificial intelligence depends on a combination of technological, organizational, and individual factors [16]. It also corresponds with research on AI in public-sector auditing, where the effectiveness of intelligent technologies has been associated with institutional capacity and appropriate implementation mechanisms [17]. The systematic literature further indicates that AI and robotic process automation frequently require changes in workflow design, organizational responsibilities, employee skills, and technology governance before their expected benefits can be realized [3, 10]. Thus, organizational readiness should be understood as an enabling infrastructure through which technological capability becomes operational audit quality.

Explainability and transparency had a significant effect on AI-assisted audit process quality ($\beta = 0.121$) and also positively predicted human oversight and professional judgment ($\beta = 0.203$). These dual effects highlight the distinctive importance of explainable AI in auditing. Audit evidence must not only be technically accurate but also interpretable, reviewable, and defensible. When auditors can understand how a model has generated a particular risk classification or anomaly signal, they are better positioned to evaluate the relevance of the output, investigate underlying transactions, document audit reasoning, and incorporate machine-generated evidence into professional conclusions. Conversely, opaque algorithmic systems may weaken professional accountability by encouraging reliance on outputs that cannot be adequately interrogated. The ethical implications of opacity and accountability in AI-supported auditing have been emphasized by Munoko and colleagues, who argued that AI introduces important issues involving transparency, responsibility, independence, privacy, and potential bias [11]. Ethical and

operational risks have also been shown to influence practitioners' willingness to adopt AI in audit settings [12]. Therefore, the present findings support the view that explainability is both a technical requirement for effective audit analytics and a professional requirement for responsible audit judgment.

Information security and system controls also significantly enhanced AI-assisted audit process quality ($\beta = 0.103$). Although its effect was smaller than that of technological reliability and data quality, the relationship remains important because AI-assisted auditing involves the processing of sensitive financial information and often depends on interconnected digital systems. Weak cybersecurity, inappropriate user access, manipulation of source data, unauthorized model changes, or failures in system controls may compromise the reliability of AI-generated audit evidence. This finding complements studies emphasizing that digital transformation in accounting and auditing produces new technological risks alongside efficiency gains [1, 8]. The result further indicates that cybersecurity and internal controls should not be treated merely as peripheral IT concerns; they form part of the evidential infrastructure supporting audit report accuracy. A secure AI system improves confidence that analytical outputs are based on authentic information and have not been altered or corrupted during processing.

AI governance and ethical-regulatory compliance significantly predicted both AI-assisted audit process quality ($\beta = 0.118$) and human oversight and professional judgment ($\beta = 0.249$), while also retaining a small direct relationship with audit report accuracy ($\beta = 0.074$). The breadth of these effects indicates that governance occupies a central coordinating role in the model. Governance mechanisms clarify who is responsible for selecting, validating, monitoring, and reviewing AI tools; establish rules for dealing with model error and bias; define acceptable uses of automated recommendations; and ensure that professional and regulatory requirements remain applicable when AI is involved. This finding is highly consistent with prior ethical analyses of AI in auditing, which have emphasized accountability, transparency, professional responsibility, privacy, and the risks associated with transferring judgment to automated systems [11]. It also aligns with evidence demonstrating that risk and ethical considerations meaningfully influence AI adoption among auditors [12]. The finding further complements the growing literature on AI-based audit judgment models, which seeks to structure the integration of intelligent technology with professional decision processes rather than allowing automation to operate independently [15]. Therefore, governance can be interpreted as the institutional mechanism that connects technological capability with professional accountability.

Another important result was that auditor digital competence was the strongest predictor of human oversight and professional judgment ($\beta = 0.286$). This finding suggests that meaningful human control over AI is possible only when auditors understand the capabilities and limitations of the technologies they are supervising. Auditors who lack knowledge of AI, data analytics, model limitations, and digital audit tools may be unable to critically challenge algorithmic recommendations and may instead become overly dependent on automated outputs. The result is consistent with evidence that AI-related training can improve audit report timeliness [13]. It also aligns with research indicating that auditor experience can strengthen the relationship between AI use and financial reporting quality [14]. These studies imply that artificial intelligence does not eliminate the value of human expertise; rather, it increases the importance of a new form of hybrid expertise combining auditing knowledge with digital and analytical competence. The present study adds to this perspective by showing that digital competence contributes to report accuracy indirectly through improved professional oversight.

Human oversight and professional judgment itself demonstrated a substantial direct effect on audit report accuracy ($\beta = 0.329$). This result confirms that AI-generated evidence cannot replace the contextual reasoning required in auditing. Auditors must determine materiality, evaluate management explanations, assess

contradictory evidence, interpret transactions within their economic context, and determine whether identified issues affect the audit opinion. These tasks involve normative and professional considerations that cannot be reduced entirely to pattern recognition. Research on AI-based audit judgment similarly recognizes the continued importance of auditor responsibility in intelligent decision environments [15]. Moreover, the moderating effect found in the present study showed that the relationship between AI-assisted audit process quality and report accuracy became stronger when human oversight was stronger. This finding provides direct empirical support for a complementary human-AI model: technological quality and professional judgment reinforce one another. Such a conclusion is consistent with the broader systematic evidence indicating that the transformation of accounting and auditing involves changes in both technological tools and professional roles [1]. Thus, the highest levels of report accuracy are likely to occur not under full automation but under carefully designed human-AI collaboration.

The mediation results further strengthened this interpretation. AI technological reliability, data quality and integrity, explainability, information security, organizational readiness, and AI governance all influenced audit report accuracy indirectly through AI-assisted audit process quality. Auditor digital competence, explainability, and governance likewise influenced report accuracy through human oversight and professional judgment. These findings help integrate areas of the literature that have often been studied separately. Previous studies have examined AI adoption, audit quality, financial reporting, ethical issues, professional training, continuous auditing, and organizational digitalization as partially distinct topics [4-6, 10]. The present model demonstrates how these factors may form interconnected pathways leading to a specific outcome: greater audit report accuracy. In this respect, the model extends prior research by moving beyond the question of whether AI improves auditing to explain the conditions and mechanisms through which such improvement occurs.

Overall, the findings suggest that AI-based audit report accuracy should be conceptualized as a sociotechnical outcome. The technological infrastructure must be reliable, the data must be trustworthy, the models must be explainable, systems must be secure, organizations must be prepared, governance must be established, and auditors must possess the digital competence necessary to maintain professional skepticism and judgment. This integrated interpretation is consistent with recent systematic reviews describing AI as a paradigm shift affecting accounting processes, audit procedures, professional competencies, organizational structures, and assurance practices simultaneously [1, 3]. It is also compatible with emerging developments toward smart data, continuous auditing, digital accounting, and expanded use of intelligent systems in accounting and assurance [2, 7]. Accordingly, the value of AI in auditing should not be evaluated solely in terms of automation or efficiency; its more consequential contribution lies in whether it improves the evidential and professional processes that ultimately support a correct and defensible audit report.

Several limitations should be considered when interpreting the findings. First, the quantitative phase was conducted among auditing, accounting, financial, and related professionals in Tehran; therefore, the institutional, technological, and professional characteristics of this setting may limit the direct generalizability of the model to other cities, countries, regulatory systems, or audit markets. Second, the quantitative data were collected through self-report questionnaires, meaning that the measures primarily represent professionals' perceptions of AI-related conditions and audit report accuracy rather than independently observed technological performance or objectively assessed audit outcomes. Common-method variance, social desirability, and differences in respondents' familiarity with artificial intelligence may therefore have influenced responses. Third, the cross-sectional design limits causal inference because the structural relationships were evaluated at one point in time. Fourth, although the qualitative phase included experts from different professional backgrounds, purposive expert sampling may not have

captured every potentially relevant perspective. Finally, AI technologies evolve rapidly, and certain dimensions of the proposed model may change in importance as intelligent audit systems, professional standards, explainability techniques, cybersecurity requirements, and regulatory frameworks continue to develop.

Future studies should replicate and extend the proposed model in different geographical and institutional contexts and compare private audit firms, public-sector auditing organizations, internal audit departments, financial institutions, and listed companies. Longitudinal research would be particularly valuable for determining whether improvements in organizational readiness, auditor digital competence, and AI governance produce measurable changes in audit report accuracy over time. Future studies should also combine survey data with objective indicators such as detected misstatements, audit adjustments, restatements, audit completion time, false-positive anomaly rates, model prediction accuracy, and subsequent regulatory findings. Experimental designs could compare audit judgments made by auditors working independently, AI systems operating independently, and human-AI collaborative teams in order to identify the conditions under which augmentation produces superior results. Further research could also examine additional moderators, including auditor experience, task complexity, organizational size, AI explainability, professional skepticism, trust in automation, regulatory maturity, and the level of AI autonomy. Comparative studies across different AI architectures and audit software platforms could additionally determine whether particular forms of machine learning, generative AI, robotic process automation, or explainable AI produce different effects on evidence quality and reporting accuracy.

Audit firms and organizations should approach AI implementation as a coordinated professional and organizational transformation rather than as a software acquisition project. Priority should be given to improving data governance, standardizing financial databases, validating the reliability of AI models, strengthening cybersecurity and access controls, and ensuring that automated analyses can be traced and explained. Audit firms should develop structured training programs that provide auditors with practical competence in data analytics, AI interpretation, model limitations, algorithmic bias, and the critical evaluation of automated recommendations. Human review should remain mandatory for material judgments and final reporting decisions, with clear procedures defining when AI outputs must be challenged, independently verified, or overridden. Organizations should also establish formal AI governance frameworks identifying responsibility for model selection, validation, monitoring, documentation, ethical compliance, and periodic performance assessment. Finally, AI should be integrated into existing audit methodology in a manner that strengthens professional skepticism and expands the quality of audit evidence rather than simply accelerating current procedures; the practical objective should be a controlled human-AI partnership in which technological capacity and professional judgment jointly enhance the accuracy, reliability, and defensibility of the final audit report.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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