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# Development and Validation of an Integrated Model of Intelligent Auditing Services Based on Artificial Intelligence and Machine Learning with a Customer Trust Enhancement Approach

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**ABSTRACT**

In recent years, auditing services have undergone fundamental transformations due to the expansion of artificial intelligence technologies, machine learning, and artificial neural networks. At the same time, challenges related to customer trust, process transparency, and the interpretability of intelligent outputs have increasingly highlighted the need to design systematic and trust-based models. The purpose of the present study is to present a comprehensive model of artificial intelligence-based auditing services with a customer trust approach. This study falls within the category of mixed-method research and is exploratory–confirmatory in nature, conducted in two qualitative and quantitative phases. In the qualitative phase, library studies and semi-structured interviews with experts in auditing, financial management, and intelligent technologies were used to identify the dimensions, components, and initial relationships of the model. The statistical population of this section consisted of 10 specialists with relevant professional experience, selected through purposive sampling and the snowball method, and the data were analyzed using thematic analysis. In the quantitative phase, the statistical population included professional auditors and customers of auditing services, and the sample size was determined as 358 participants. The data collection instrument was a researcher-made questionnaire based on a five-point Likert scale. Descriptive statistics, structural equation modeling, and advanced machine learning-based analysis were used to analyze the data. The results showed that the key criteria for designing an artificial intelligence-oriented auditing model and the technical sub-criteria of intelligent auditing played the greatest role in explaining the benefits of auditing services and strengthening customer trust. Furthermore, the evaluation of fit indices and the results of machine learning models indicated desirable predictive accuracy and coherence of the final research model.

**Keywords:** auditing services, artificial intelligence, customer trust, machine learning

## Introduction

The auditing profession is undergoing a profound technological transformation as artificial intelligence, machine learning, deep learning, data analytics, and cloud-based intelligent systems increasingly reshape the logic, scope, and execution of audit services. Traditionally, auditing has relied heavily on sampling procedures, professional


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judgment, retrospective testing, manual documentation, and standardized assurance protocols. Although these mechanisms have established the institutional credibility of audit practice, contemporary business environments are characterized by high-volume transactions, real-time digital operations, complex enterprise systems, platform-based financial services, and growing stakeholder expectations regarding transparency, responsiveness, and reliability. In such conditions, conventional audit models may face limitations in detecting anomalies, processing large and heterogeneous datasets, identifying complex risk patterns, and responding to clients' expectations for timely and interpretable assurance. Artificial intelligence has therefore emerged not merely as a technological tool but as a strategic capability that can alter the epistemic foundations of auditing by enabling continuous monitoring, predictive risk assessment, automated evidence evaluation, fraud detection, and intelligent reporting (1-4).

The adoption of artificial intelligence in auditing is part of a wider digital transformation occurring across accounting, taxation, financial reporting, and financial service ecosystems. Industry 4.0 technologies have intensified the automation of routine accounting and audit tasks, while also creating new demands for auditors to understand algorithms, data architectures, cybersecurity risks, and digital governance mechanisms (5-7). In this context, AI-based audit systems can improve the efficiency of audit procedures by reducing repetitive manual work, expanding the scope of audit testing, enhancing analytical depth, and supporting auditors in identifying abnormal patterns that may not be detectable through traditional techniques. Previous studies have highlighted the role of AI in transforming financial statement auditing objectives, strengthening evidence-gathering processes, and improving audit quality through automation and intelligent analytics (8-10). Nevertheless, the technological promise of AI in auditing cannot be separated from its organizational, ethical, regulatory, and trust-related implications.

One of the most significant potential contributions of artificial intelligence to auditing is its capacity to increase audit quality by improving accuracy, coverage, timeliness, and risk sensitivity. Machine learning algorithms can process large datasets, identify hidden correlations, classify transactions, detect outliers, and support fraud prevention through pattern recognition. Internal audit functions, in particular, may benefit from AI-based systems that strengthen fraud detection and prevention, improve control monitoring, and provide more sophisticated risk indicators (11). Similarly, the integration of cloud-based artificial intelligence into auditing has been associated with opportunities for scalable data processing, remote audit execution, and improved analytical capacity (12). However, the use of AI also requires appropriate technical infrastructure, data governance, model validation, audit trail documentation, and professional oversight. Without these conditions, AI may increase rather than reduce uncertainty, particularly when auditors and clients cannot understand or verify algorithmic outputs.

The issue of trust is therefore central to the development of intelligent auditing services. Audit services are fundamentally trust-producing professional services: they are designed to reduce information asymmetry, enhance financial credibility, and provide assurance to users of financial information. When AI becomes embedded in audit processes, trust is no longer limited to trust in the auditor, the audit firm, or professional standards; it also extends to trust in data quality, algorithmic logic, model transparency, system security, and the interpretability of outputs. Research on AI auditing professionals suggests that trust in AI should not be treated as a superficial add-on or a low-cost compliance exercise, but as a core element of responsible AI deployment in assurance contexts (13). In financial services more broadly, algorithmic trust depends on ethical governance, regulatory safeguards, explainability, privacy protection, and accountability mechanisms (14). Accordingly, the design of AI-based auditing models must incorporate trust-building criteria from the beginning rather than treating trust as a post-implementation concern.

Customer trust is especially important because audit clients and users increasingly expect intelligent services to provide not only efficiency but also transparency, security, accessibility, service quality, and reliable communication. Studies of AI-based customer services indicate that adoption intention is influenced by users' perceptions of usefulness, trust, service quality, and contextual readiness (15). In digital banking and financial services, trust and data privacy are decisive factors in shaping customers' perceptions of AI-enabled services (16). Similarly, AI-driven financial inclusion depends on trust, security, accessibility, and service quality, suggesting that technological capability alone is insufficient unless users believe that AI systems are reliable, secure, and beneficial (17). These insights are highly relevant to auditing because clients may accept AI-based audit services only when they perceive them as accurate, understandable, secure, professionally supervised, and aligned with their interests.

The service literature also shows that AI-mediated interactions can reshape customer attitudes and behavioral responses. Conversational AI and AI-mediated communication influence trust formation in online consumers by affecting perceived responsiveness, personalization, transparency, and social presence (18, 19). In FinTech services, conversational AI can strengthen trust and adoption when users perceive it as reliable, useful, and capable of supporting financial decision-making (20). Research on AI-driven customer support similarly shows that customer attitudes toward AI solutions depend on perceived service quality, ease of use, problem-solving capacity, and confidence in the system (21). Although auditing differs from routine customer support, these findings underline a broader principle: clients' willingness to rely on AI-enabled professional services depends on both technical performance and the perceived trustworthiness of the service encounter.

In service industries, AI affects customer satisfaction not only directly but also through service quality, and this relationship may be moderated by customer trust (22). In the banking sector, AI-driven self-service technologies have been linked to enhanced customer experience outcomes, particularly when they improve convenience, responsiveness, and perceived value (23). These findings suggest that intelligent auditing services should be evaluated not only through internal audit efficiency metrics but also through client-centered outcomes such as perceived transparency, satisfaction, confidence, and trust in audit conclusions. Furthermore, AI and consumer trust have been examined in relation to pro-environmental behavior and broader digital decision-making contexts, showing that trust can mediate the relationship between AI-enabled communication and behavioral acceptance (24). Such evidence supports the argument that customer trust must be treated as a key outcome and design principle in AI-based auditing models.

Despite the increasing relevance of AI in audit practice, its implementation remains uneven and faces multiple barriers. Audit professionals may recognize the potential of data analysis and artificial intelligence but still hesitate to adopt these technologies due to limited technical skills, insufficient organizational readiness, regulatory ambiguity, cost constraints, data quality issues, and uncertainty about professional responsibility (25). Studies on the auditing profession show that AI is changing audit work, but the pace of transformation depends on institutional readiness, education, technological infrastructure, and professional adaptation (26). In Jordan, the impact of AI on auditing has been evaluated from the perspective of the profession, emphasizing both opportunities for audit improvement and concerns regarding implementation, competence, and governance (27). Therefore, AI-based auditing cannot be reduced to software adoption; it requires an integrated model that connects technological sub-criteria, organizational barriers, professional competencies, and trust-related mechanisms.

Educational and professional adaptation also represent important prerequisites for intelligent auditing. The rise of AI requires accounting and audit education to be revised in order to prepare future auditors for data-driven assurance environments, algorithmic reasoning, and digital risk assessment (28). If auditors lack sufficient knowledge of AI systems, they may either over-rely on automated outputs or underuse valuable analytical tools due to distrust or uncertainty. Both outcomes can undermine audit quality. Grounded theory research on AI factors in auditing has identified multiple effective elements in improving audit processes, including technical capabilities, professional readiness, organizational support, and methodological adaptation (29). Thus, a comprehensive intelligent audit model must preserve the role of human judgment while enabling auditors to use AI as an augmentative, rather than purely substitutive, technology.

Ethical and regulatory challenges constitute another major dimension of AI-based auditing. AI systems may generate biased outputs, rely on incomplete or poor-quality data, produce opaque decisions, or create accountability gaps when responsibility for audit conclusions becomes distributed between human auditors and intelligent systems. Research on AI in financial auditing has emphasized both efficiency gains and ethical and regulatory challenges, particularly with respect to transparency, accountability, professional standards, and compliance (30). Similarly, opportunities and challenges in integrating AI into financial auditing include improved efficiency and fraud detection, but also concerns related to implementation cost, data protection, regulatory uncertainty, and the need for human oversight (31). These challenges imply that the validity of an AI-oriented audit model depends not only on predictive performance but also on governance arrangements that make outputs explainable, auditable, and professionally defensible.

A major methodological development in this field is the use of hybrid analytical approaches that combine structural equation modeling with artificial neural networks. In audit research, SEM-ANN analysis has been used to examine the impact of AI-based audit services on client trust, demonstrating that both linear relationships and nonlinear predictive patterns can be relevant in explaining trust outcomes (32). This is particularly important because customer trust in AI-based auditing is unlikely to be formed through a single direct pathway. Instead, it may emerge through interactions among perceived accuracy, transparency, data security, human oversight, service quality, implementation barriers, and organizational acceptance. Machine learning-based analysis can therefore complement conventional statistical modeling by identifying complex patterns among technical, organizational, and perceptual variables. For this reason, the validation of an intelligent auditing services model requires both theory-driven structural modeling and data-driven predictive analysis.

Innovation climate also plays a central role in AI adoption in financial service-oriented contexts. When organizations support experimentation, learning, digital transformation, and cross-functional collaboration, they are more likely to adopt AI effectively and integrate it into service delivery (33). This insight is directly applicable to auditing firms and client organizations because AI-based audit services require alignment between audit methodology, data infrastructure, client cooperation, professional standards, and technological governance. If the organizational climate is resistant to innovation, even technically advanced AI tools may fail to generate trust or practical value. Conversely, when innovation climate is supported by training, gradual implementation, transparent communication, and risk management, AI can become a credible component of audit service modernization.

The literature therefore reveals both a strong rationale and a clear research gap. On the one hand, prior studies have examined AI adoption in auditing, AI applications in enterprise auditing, cloud-based AI integration, fraud detection, audit quality, customer trust in digital financial services, and AI-mediated service interactions (3, 11, 12, 16, 21). On the other hand, fewer studies have provided an integrated, empirically validated model that simultaneously captures the technical sub-criteria of intelligent auditing, operational implementation barriers, customer expectations, trust-building challenges, output interpretability, AI acceptance strategies, and the benefits of AI in audit service improvement. Existing studies often focus either on technological capabilities, professional adoption, ethical concerns, or customer trust, while the interaction among these dimensions remains underdeveloped. This fragmentation limits the ability of audit firms, regulators, and client organizations to design AI-based auditing services that are technically robust, professionally acceptable, and trust-enhancing.

Accordingly, the present study is positioned at the intersection of auditing, artificial intelligence, machine learning, customer trust, and management of professional services. It assumes that intelligent auditing is not simply a technological upgrade but a multidimensional service innovation requiring the coordination of technical infrastructure, organizational readiness, human expertise, ethical governance, and customer-centered trust mechanisms. The study responds to the need for a comprehensive framework that can explain how AI-based auditing services may improve audit quality and service benefits while also addressing the barriers and trust-related concerns that shape client acceptance. By combining qualitative thematic analysis, structural equation modeling, and neural network-based analysis, the study seeks to generate and validate a model that is both conceptually grounded and empirically testable. This integrated approach is particularly appropriate because the phenomenon under investigation involves subjective perceptions, professional judgments, organizational conditions, and complex nonlinear relationships among variables.

The aim of this study is to develop and validate an integrated model of intelligent auditing services based on artificial intelligence and machine learning with an emphasis on strengthening customer trust.

## Methods and Materials

The research method of this study was designed based on an exploratory mixed-method approach and consists of two qualitative and quantitative sections that were implemented sequentially and complementarily. In the first phase, using a qualitative method and conducting semi-structured interviews with experts in auditing, financial management, and artificial intelligence-based technologies, the researcher identified the components, dimensions, and requirements of an artificial intelligence-based auditing services model with a customer trust approach. Sampling in this section was carried out purposively and then through snowball sampling and continued until theoretical saturation was reached; accordingly, after 10 specialized interviews, the qualitative data reached stability and recurrence. The data in this section were analyzed using thematic analysis, during which the interview data underwent initial coding, axial coding, and then the extraction of main and sub-themes, leading to the formation of the initial conceptual framework of the study.

In the quantitative phase, the findings of the qualitative phase were transformed into a measurable instrument and tested through a structured questionnaire among a broader statistical population, including professional auditors and customers of auditing services. The questionnaire was designed based on a five-point Likert scale, and after its content validity was confirmed by experts, its construct validity was examined using confirmatory factor analysis in SmartPLS software. The reliability of the instrument was also confirmed through Cronbach's alpha coefficient. Sampling in the quantitative phase was conducted using cluster and convenience sampling, and the sample size was determined using Cochran's formula; ultimately, 358 valid questionnaires were collected for the final analysis. To test the research model, structural equation modeling was first implemented, and the relationships among variables were examined through indices of convergent validity, discriminant validity, and model fit.

To improve the accuracy of the analysis and examine the proposed model at a more advanced level, deep learning-based analysis was also employed. In this section, an artificial neural network with a single-layer perceptron structure was implemented in the MATLAB environment to identify nonlinear and complex patterns among the research variables and to increase the predictive accuracy of the model. The data were divided into training and testing sets using 10-fold cross-validation, and model performance was evaluated based on the RMSE index, the results of which indicated the acceptable accuracy of the deep learning model. The combination of qualitative, quantitative, and neural network-based analytical methods enabled the study to benefit from a comprehensive approach and allowed the final model of artificial intelligence-based auditing services to be presented with greater reliance on empirical evidence and multilevel analyses.

## Findings and Results

In the qualitative section of the study, data were collected through interviews with 10 experts in accounting, auditing, financial management, and financial technologies. The experts were selected based on their professional experience, scientific activity, and direct relevance to the research topic, and they were drawn from a diverse set of universities, private and public auditing firms, industrial and service companies, and companies active in the field of financial technologies. Their mean age was approximately 45 years, with an age range between 36 and 58 years. In terms of educational level, the majority held doctoral degrees, while the others held master's degrees. Their areas of expertise included auditing, financial management, information systems, risk management, and applications of artificial intelligence in financial services, and this diversity of expertise contributed to the richness of the qualitative analyses of the study.

In the quantitative section of the study, the demographic characteristics of 358 respondents were examined. The results showed that customers of auditing services accounted for the largest proportion of responses, followed by professional auditors. In terms of gender, the majority of respondents were male, and in the age analysis, the highest frequency belonged to individuals under 30 years old, although a relatively balanced composition of other age groups was also observed. The educational level of the population under study was mainly at the master's and doctoral levels, and a considerable proportion of respondents had more than 15 years of work experience. In addition, familiarity with artificial intelligence in auditing was mostly reported at the “moderate” level, and the use of artificial intelligence-based tools among participants was mainly limited or occasional, indicating the emerging nature of the practical application of this technology in auditing environments.

In this study, thematic analysis based on the framework of Braun and Clarke (2006) was used to identify the dimensions and components of the artificial intelligence-based auditing services model with a customer trust approach. This method was implemented as a systematic six-stage process. In the first stage, the texts of the semi-structured interviews were read and reviewed several times so that the researcher could achieve a deep understanding of the data. In the second stage, key concepts were extracted and initial codes were generated. Overall, a considerable number of open codes were identified from the experts' statements, reflecting their views on the challenges of traditional auditing, customer expectations, the benefits of artificial intelligence, model design criteria, technical infrastructures, and implementation barriers. In the third stage, similar codes were aggregated and organized into initial themes. Then, in the fourth stage, these themes were reviewed, merged, or refined to ensure their conceptual coherence and alignment with the research objectives. In the fifth stage, the final themes were defined and named, and the conceptual framework of the study was formed. The results of thematic analysis led to the identification of several main themes, including trust-building challenges in traditional auditing services, customer expectations of artificial intelligence in auditing, the benefits of artificial intelligence in improving auditing services, key criteria for designing an artificial intelligence-oriented auditing model, technical sub-criteria for intelligent auditing, strategies for ensuring the comprehensibility of and trust in outputs, operational barriers to implementing the model, and strategies for increasing the acceptance of artificial intelligence.

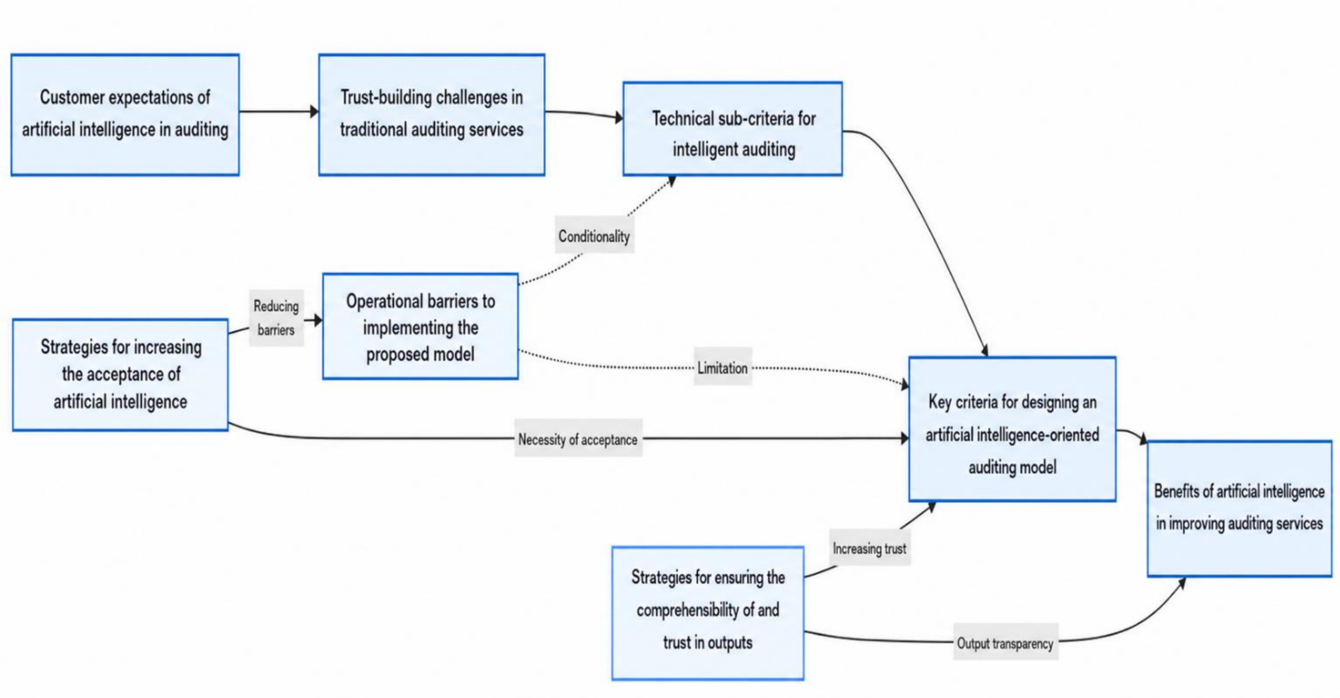


**Figure 1. Conceptual model of artificial intelligence-based auditing services with a customer trust approach**

These themes formed the basis for designing the questionnaire for the quantitative section and developing the final research model, providing an integrated framework for explaining the model of artificial intelligence-based auditing services centered on customer trust.

**Table 1. Main Themes and Definitions**

| Main Theme | Definition |
|---|---|
| Trust-building challenges in traditional auditing services | Problems and barriers that reduce customers' trust in traditional auditing services, including insufficient transparency, unequal quality, technological limitations, and communication challenges |
| Customer expectations of artificial intelligence in auditing | Customers' expectations and needs for accuracy, speed, transparency, and traceability in artificial intelligence-based auditing services |
| Benefits of artificial intelligence in improving auditing services | Positive aspects and added value of artificial intelligence in increasing the accuracy, quality, coverage, and efficiency of auditing services |
| Key criteria for designing an artificial intelligence-oriented auditing model | Key indicators and criteria used to design and evaluate an artificial intelligence-based auditing model |
| Technical sub-criteria for intelligent auditing | Technical details and algorithmic and software infrastructures required for the successful implementation of intelligent auditing |
| Strategies for ensuring the comprehensibility of and trust in outputs | Methods and measures for increasing the transparency and trustworthiness of results generated by artificial intelligence systems |
| Operational barriers to implementing the proposed model | Operational limitations and problems that may prevent the successful implementation of the intelligent auditing system |
| Strategies for increasing the acceptance of artificial intelligence | Activities and recommendations that can be used to promote the acceptance and effective use of artificial intelligence in organizations |

Based on the results of descriptive statistics (Table 2), the highest mean was related to the component “structural and communication challenges,” with a value of 87.38 and a relatively high standard deviation, indicating the importance of these challenges and, at the same time, heterogeneity in respondents’ views in this regard. In addition, the components “process transparency and reporting,” “expectations of artificial intelligence,” and “quality and accuracy improvement” had relatively high mean scores above 20, indicating respondents’ positive attitudes toward the role of artificial intelligence in enhancing transparency, increasing accuracy, and improving the quality of auditing services. In contrast, relatively lower mean scores in components such as “preserving the human role,” “compliance and standards,” and “quality control and review” indicate concerns and professional caution regarding the complete replacement of human judgment and the adaptive and supervisory challenges involved in using artificial intelligence. From a technical and operational perspective, higher mean scores in components such as “advanced analytics,” “learning algorithms,” “intelligent processing and analysis,” and “infrastructure and tools” indicate relative readiness to adopt intelligent solutions, whereas moderate values in components such as “costs and resources,” “data-driven challenges,” and “data security and governance” reflect operational, financial, and data-related barriers to the widespread implementation of artificial intelligence in auditing. Overall, the descriptive statistics show that the general attitude toward the application of artificial intelligence is positive; however, the full realization of its capacities requires strengthening infrastructures, standardizing data, providing training and cultural development, and paying serious attention to legal and regulatory considerations.

**Table 2. Descriptive Statistics of the Components**

| Components | Mean | Maximum | Minimum | Standard Deviation |
|---|---|---|---|---|
| Process transparency and reporting | 20.66 | 25 | 11 | 2.844 |
| Inequality and heterogeneous quality | 3.97 | 5 | 1 | 0.987 |
| Structural and communication challenges | 87.38 | 105 | 60 | 9.064 |
| Expectations of artificial intelligence | 20.56 | 25 | 10 | 3.204 |
| Quality and accuracy improvement | 20.53 | 25 | 10 | 3.155 |
| Expansion of scope and coverage | 12.62 | 15 | 8 | 1.776 |
| Advanced analytics | 25.48 | 30 | 18 | 2.676 |
| Automation and visualization | 12.28 | 15 | 6 | 1.950 |
| Model accuracy and quality | 17.08 | 20 | 11 | 1.949 |
| Transparency and interpretability | 12.11 | 15 | 7 | 1.592 |
| Preserving the human role | 8.42 | 10 | 6 | 1.171 |
| Data security and governance | 13.20 | 15 | 6 | 1.538 |
| Compliance and standards | 8.58 | 10 | 5 | 1.213 |
| Learning algorithms | 16.77 | 20 | 11 | 2.163 |
| Intelligent processing and analysis | 15.94 | 20 | 10 | 2.574 |
| Infrastructure and tools | 16.12 | 20 | 7 | 2.447 |
| Interpretability and visualization | 12.53 | 15 | 5 | 1.937 |
| Quality control and review | 8.65 | 10 | 4 | 1.229 |
| Documentation and simplification | 12.16 | 15 | 5 | 2.184 |
| Data-driven challenges | 11.65 | 15 | 5 | 1.970 |
| Costs and resources | 12.10 | 15 | 6 | 2.053 |
| Culture and organization | 4.15 | 5 | 1 | 0.817 |
| Legal and regulatory issues | 12.46 | 15 | 7 | 1.982 |
| Legacy technology | 3.92 | 5 | 1 | 0.813 |
| Lack of standardized data | 4.15 | 5 | 1 | 0.738 |
| Training and cultural development | 11.97 | 15 | 5 | 2.034 |
| Gradual implementation | 16.80 | 20 | 9 | 2.499 |
| Total | 358 | | | |

First, the reliability of the questionnaire was examined. The overall Cronbach’s alpha coefficient of the questionnaire was 0.970 for 103 items, indicating very desirable internal consistency and high instrument reliability.

Moreover, the results of the measurement model showed that all indicators had factor loadings above 0.30; therefore, none of the items were removed. The examination of the internal reliability of the constructs also indicated that the Cronbach's alpha values of all dimensions were above 0.7, except for one construct with a value close to the acceptable threshold. In addition, the composite reliability of the constructs ranged from 0.830 to 0.898, indicating appropriate reliability and construct stability. Furthermore, the AVE values of all constructs were above 0.5, confirming the convergent validity of the measurement model. In addition, the Fornell–Larcker matrix showed that the square root of the AVE of each construct was greater than its correlations with other constructs; therefore, the discriminant validity of the model was also confirmed.

At the stage of structural model evaluation, the coefficient of determination values ($R^2$) were reported to range from 0.381 to 0.676, indicating the appropriate explanatory power of the endogenous constructs. In addition, the predictive relevance index ($Q^2$) was positive for all constructs and ranged from 0.237 to 0.440, indicating the appropriate predictive power of the model. Finally, the overall goodness-of-fit index of the model (GOF) was obtained as 0.63, which, according to the criterion of Wetzels et al. (2009), indicates the strong fit of the research model and the appropriate quality of the measurement and structural sections. Accordingly, it can be concluded that the research model is in a highly desirable condition in terms of reliability, validity, explanatory power, and predictive power, and that the instrument and model structure possess the necessary validity for the final analyses.

Effect size indicates the strength of the relationship between variables, and the range of this coefficient is between 0 and 1. The closer this value is to 1, the stronger the relationships between the variables are. T values between -1.96 and 1.96 indicate the absence of a significant effect between the relevant latent variables. T values between the absolute value of 1.96 and 2.576 indicate a significant effect between the relevant latent variables with more than 95% confidence. T values equal to or greater than the absolute value of 2.576 indicate a significant effect between the relevant latent variables with more than 99% confidence.

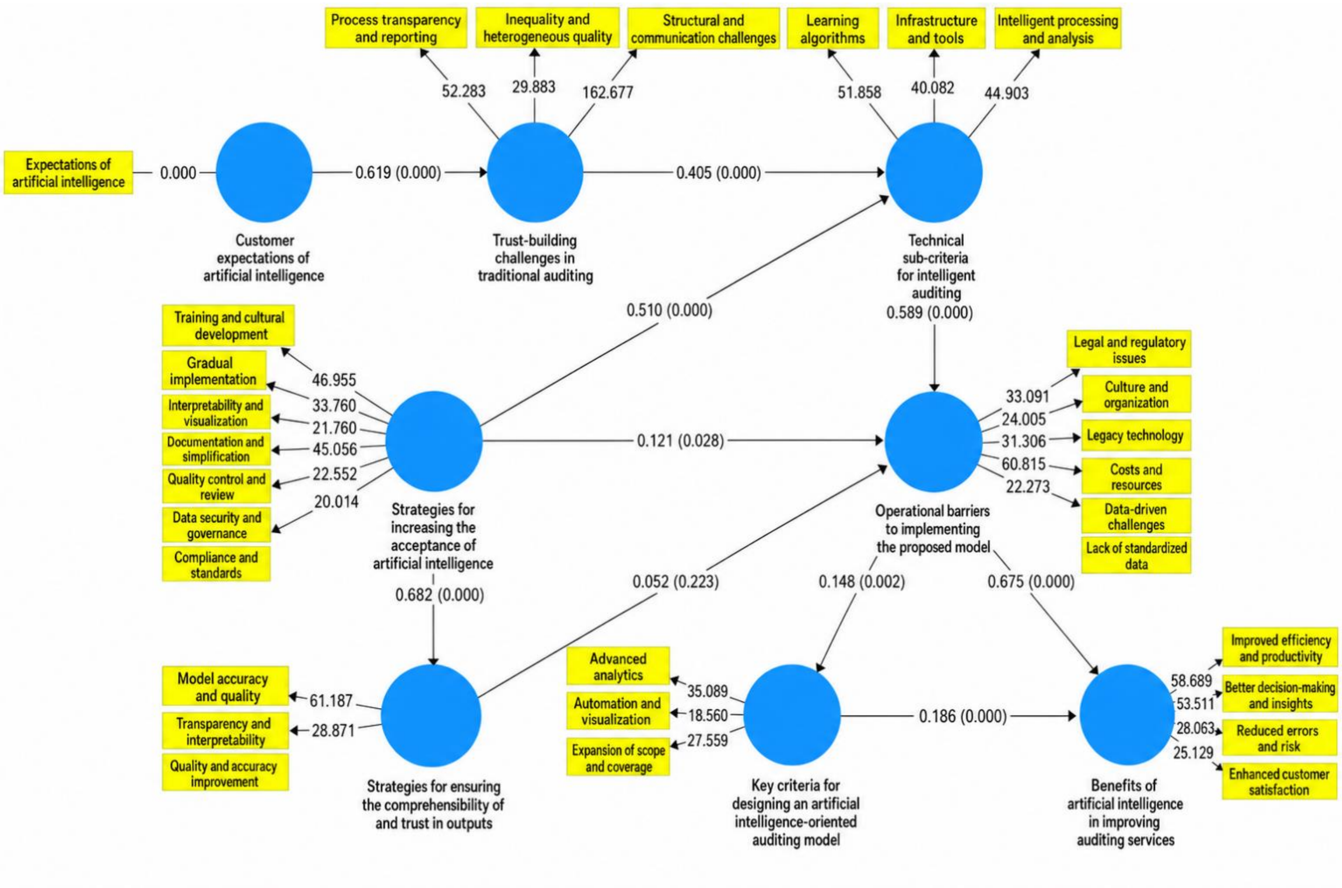


**Figure 2. Path coefficients and significance level values of the relationships among dimensions in the model**

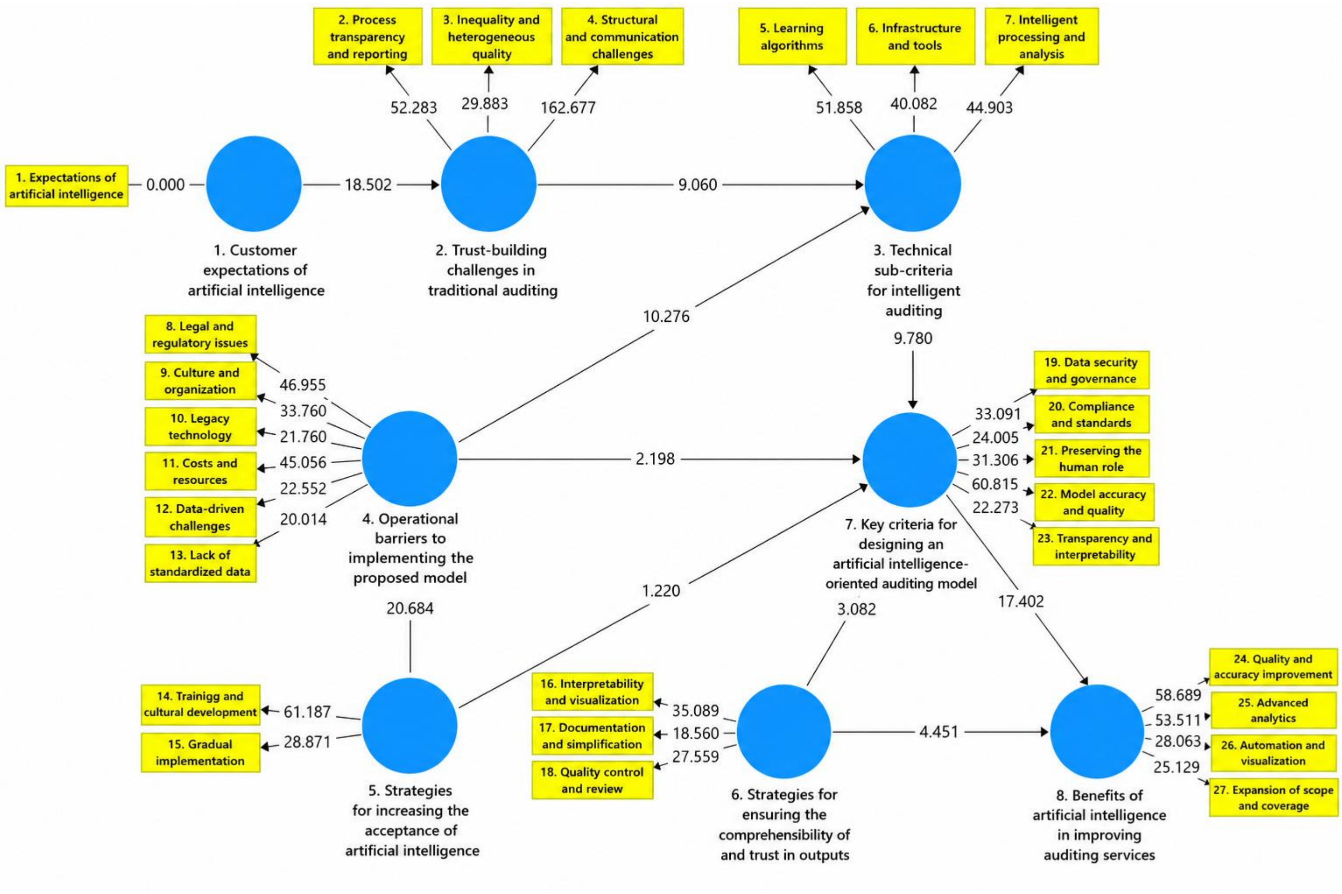


**Figure 3. T values of the dimensions in the model**

**Table 3. Examination of Path Coefficients (Beta) and Their Significance**

| Paths | Path Coefficients (Beta) | T Value | Significance Level | Result |
|---|---|---|---|---|
| Customer expectations of artificial intelligence on trust-building challenges in traditional auditing | 0.619 | 18.502 | 0.000 | Confirmed |
| Strategies for ensuring the comprehensibility of and trust in outputs on the benefits of artificial intelligence in improving auditing services | 0.186 | 4.451 | 0.000 | Confirmed |
| Strategies for ensuring the comprehensibility of and trust in outputs on the key criteria for designing an artificial intelligence-oriented auditing model | 0.148 | 3.082 | 0.002 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on the key criteria for designing an artificial intelligence-oriented auditing model | 0.052 | 1.220 | 0.223 | Not confirmed |
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model | 0.682 | 20.684 | 0.000 | Confirmed |
| Technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model | 0.589 | 9.780 | 0.000 | Confirmed |
| Key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.675 | 17.402 | 0.000 | Confirmed |
| Operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing | 0.510 | 10.276 | 0.000 | Confirmed |
| Operational barriers to implementing the proposed model on the key criteria for designing an artificial intelligence-oriented auditing model | 0.121 | 2.198 | 0.028 | Confirmed |
| Trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing | 0.405 | 9.060 | 0.000 | Confirmed |

Table 3 shows that most of the structural paths of the model were statistically significant, and the paths of the research model were widely confirmed. The strongest effect was related to the path “strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model,” with a beta coefficient of 0.682 and a T value of 20.684, indicating the highly prominent role of this variable in reducing or explaining implementation barriers. In addition, the path “customer expectations of artificial intelligence on trust-building challenges in traditional auditing,” with a beta of 0.619 and a T value of 18.502, shows that customer expectations have a considerable effect on the formation or intensification of trust-related challenges in traditional auditing. Furthermore, the significant effect of “key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services” (β = 0.675) indicates the central role of appropriate model design in realizing the practical benefits of artificial intelligence in auditing services. In contrast, only the path “strategies for increasing the acceptance of artificial intelligence on the key criteria for designing an artificial intelligence-oriented auditing model,” with a T value of 1.220 and a significance level of 0.223, was not significant, and the related hypothesis was rejected. This indicates that increasing the acceptance of artificial intelligence does not necessarily lead directly to the improvement of the design criteria of the auditing model. Other paths, although with moderate to weak effect sizes, such as β = 0.121 and β = 0.148, were statistically significant and indicate valid causal relationships among the constructs. Overall, the results show that the structural model of the study has an appropriate fit and that the roles of technical variables, model design, and trust-building factors in explaining the benefits and barriers of implementing artificial intelligence-based auditing are well confirmed.

**Table 4. Examination of Path Coefficients (Beta) and the Significance of Specific Indirect Effects**

| Paths | Path Coefficients (Beta) | T Value | Significance Level | Result |
|---|---|---|---|---|
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing | 0.348 | 8.580 | 0.000 | Confirmed |
| Customer expectations of artificial intelligence on trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing | 0.251 | 7.741 | 0.000 | Confirmed |
| Strategies for ensuring the comprehensibility of and trust in outputs on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.100 | 3.308 | 0.001 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.035 | 1.234 | 0.218 | Not confirmed |
| Operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.203 | 8.448 | 0.000 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.138 | 7.207 | 0.000 | Confirmed |
| Technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.398 | 7.348 | 0.000 | Confirmed |
| Trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.161 | 4.960 | 0.000 | Confirmed |
| Customer expectations of artificial intelligence on trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence- | 0.100 | 4.714 | 0.000 | Confirmed |

| | | | | |
|---|---|---|---|---|
| oriented auditing model on the benefits of artificial intelligence in improving auditing services | | | | |
| Operational barriers to implementing the proposed model on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.082 | 2.220 | 0.027 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model on the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of artificial intelligence in improving auditing services | 0.056 | 2.143 | 0.033 | Confirmed |
| Operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model | 0.300 | 10.309 | 0.000 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model | 0.205 | 8.566 | 0.000 | Confirmed |
| Trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model | 0.239 | 5.728 | 0.000 | Confirmed |
| Customer expectations of artificial intelligence on trust-building challenges in traditional auditing on technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model | 0.148 | 5.326 | 0.000 | Confirmed |
| Strategies for increasing the acceptance of artificial intelligence on operational barriers to implementing the proposed model on the key criteria for designing an artificial intelligence-oriented auditing model | 0.082 | 2.131 | 0.034 | Confirmed |

Table 4 shows that a major portion of the specific indirect effects in the research model were statistically significant, and the mediation mechanisms defined in the model were well confirmed. The highest indirect effect was related to the path “technical sub-criteria for intelligent auditing ← key criteria for designing an artificial intelligence-oriented auditing model ← benefits of artificial intelligence in improving auditing services,” with a beta coefficient of 0.398 and a T value of 7.348, indicating the central role of technical infrastructures and requirements in realizing the final benefits of artificial intelligence through the appropriate design of the auditing model. In addition, multistage paths involving “strategies for increasing the acceptance of artificial intelligence” and “operational barriers” had considerable beta coefficients and high T values, indicating the importance of mediating variables in transferring effects to the final outcomes of the model. In contrast, only the indirect path “strategies for increasing the acceptance of artificial intelligence ← key criteria for designing an artificial intelligence-oriented auditing model ← benefits of artificial intelligence in improving auditing services,” with a significance level of 0.218, was not significant and was not confirmed. This result indicates that the acceptance of artificial intelligence alone, without passing through operational barriers and strengthening technical sub-criteria, does not have a significant effect on the benefits derived from designing the auditing model. Overall, the findings emphasize the decisive role of mediating variables, especially operational barriers, trust-building challenges, and technical sub-criteria, in shaping the chain of indirect effects and show that realizing the benefits of artificial intelligence in auditing requires a systemic and staged approach.

In this section, to complement the results obtained from structural equation modeling and to examine complex and nonlinear patterns among the research variables, a deep learning approach based on artificial neural networks was used. A fundamental prerequisite for implementing deep learning models is the examination of data distribution and ensuring the statistical quality of input variables; therefore, in the first step, descriptive statistical indices, including mean, standard deviation, skewness, and kurtosis, were examined for all variables, the results of which are presented in the descriptive statistics table. Based on the results of descriptive statistics, all variables had the same sample size of 358 valid observations, and their range of variation was consistent with the five-point Likert scale and the aggregation of items. Within the deep learning framework, variables related to expectations of artificial intelligence, process transparency and reporting, advanced analytics, automation and visualization, learning algorithms, and intelligent processing and analysis were considered the main inputs of the neural network.

On the other hand, variables related to implementation challenges and barriers, including “structural and communication challenges,” “data-driven challenges,” “costs and resources,” “legacy technology,” and “lack of standardized data,” also showed considerable dispersion.

In the next stage, the described data were used as inputs to the artificial neural network to identify hidden patterns among technical, organizational, and perceptual components and the final outcome of the study, namely the benefits of artificial intelligence in improving auditing services. The relatively high mean values in variables such as “quality and accuracy improvement,” “expansion of scope and coverage,” and “model accuracy and quality” indicate that the expected output of the neural network has strong empirical support in the data and that the relationships between inputs and output are not merely linear and simple.

**Table 5. Relative Importance of Sub-Themes in the Artificial Neural Network (ANN)**

| Rank | Input Variable | Relative Importance | Normalized Importance (%) |
|---|---|---|---|
| 1 | Advanced analytics | 0.142 | 100 |
| 2 | Process transparency and reporting | 0.131 | 92 |
| 3 | Model accuracy and quality | 0.125 | 88 |
| 4 | Learning algorithms | 0.119 | 84 |
| 5 | Intelligent processing and analysis | 0.112 | 79 |
| 6 | Automation and visualization | 0.106 | 75 |
| 7 | Interpretability and visualization | 0.098 | 69 |
| 8 | Data security and governance | 0.091 | 64 |
| 9 | Quality control and review | 0.085 | 60 |
| 10 | Infrastructure and tools | 0.081 | 57 |
| 11 | Quality and accuracy improvement | 0.078 | 55 |
| 12 | Expansion of scope and coverage | 0.073 | 51 |
| 13 | Preserving the human role | 0.069 | 49 |
| 14 | Compliance and standards | 0.064 | 45 |
| 15 | Documentation and simplification | 0.061 | 43 |
| 16 | Training and cultural development | 0.057 | 40 |
| 17 | Gradual implementation | 0.054 | 38 |
| 18 | Data-driven challenges | 0.050 | 35 |
| 19 | Costs and resources | 0.047 | 33 |
| 20 | Culture and organization | 0.044 | 31 |
| 21 | Legal and regulatory issues | 0.041 | 29 |
| 22 | Inequality and heterogeneous quality | 0.038 | 27 |
| 23 | Legacy technology | 0.034 | 24 |
| 24 | Lack of standardized data | 0.031 | 22 |
| 25 | Structural and communication challenges | 0.028 | 20 |
| 26 | Expectations of artificial intelligence | 0.026 | 18 |

The results of Table 5 show that the artificial neural network assigned the greatest weight and importance to variables related to analytical capability, transparency, and the quality of artificial intelligence models. The variable “advanced analytics,” with the highest normalized importance of 100%, was identified as the most influential factor in predicting the benefits of artificial intelligence in auditing services. This result shows that, from a machine learning perspective, the ability to perform complex analyses and extract advanced patterns plays a central role in realizing the added value of intelligent auditing. In addition, variables such as “process transparency and reporting,” “model accuracy and quality,” and “learning algorithms” ranked next, indicating the importance of trustworthiness, accuracy of results, and algorithmic structure in the performance of artificial intelligence-based auditing systems. In contrast, variables such as "legacy technology," "lack of standardized data," and "structural and communication challenges" had lower relative importance, indicating that these factors mainly play an indirect inhibiting role and that their effects are transmitted through technical variables and model design in the neural network. Overall, these findings are consistent with the results of structural equation modeling and show that machine learning, by identifying nonlinear patterns, emphasizes the central role of technical and analytical components in the success of artificial intelligence-oriented auditing.

## Discussion and Conclusion

The findings of the present study provide empirical support for the development and validation of an integrated model of intelligent auditing services based on artificial intelligence and machine learning with a customer trust enhancement approach. The qualitative phase identified eight core themes: trust-building challenges in traditional auditing services, customer expectations of artificial intelligence in auditing, benefits of artificial intelligence in improving auditing services, key criteria for designing an artificial intelligence-oriented auditing model, technical sub-criteria for intelligent auditing, strategies for ensuring the comprehensibility of and trust in outputs, operational barriers to implementing the proposed model, and strategies for increasing the acceptance of artificial intelligence. These themes indicate that AI-based auditing should not be conceptualized merely as a technological modernization of audit procedures, but rather as a multidimensional service innovation that combines technical infrastructure, professional judgment, organizational readiness, ethical governance, and client-centered trust mechanisms. This interpretation is consistent with previous research showing that AI adoption in auditing is shaped by technological capacity, professional acceptance, audit quality concerns, and organizational preparedness (1-4). The emergence of trust as a central dimension also aligns with studies emphasizing that AI in audit and financial services requires explainability, accountability, data privacy, and confidence in algorithmic outputs (13, 14, 16).

The descriptive results showed that respondents generally held a positive view of the application of artificial intelligence in auditing, particularly in relation to process transparency and reporting, expectations of artificial intelligence, quality and accuracy improvement, advanced analytics, learning algorithms, intelligent processing and analysis, and infrastructure and tools. These results indicate that professional auditors and audit clients perceive AI as a potentially valuable mechanism for improving the efficiency, scope, and analytical depth of audit services. Such findings are consistent with prior studies reporting that AI can expand audit coverage, reduce manual workload, improve anomaly detection, support fraud prevention, and enhance audit evidence evaluation (8, 9, 11, 31). The relatively high importance attributed to analytical and technical components also supports the argument that AI-based audit systems can strengthen audit quality by enabling broader and more precise data analysis than conventional sampling-based procedures (7, 10, 27).

At the same time, the descriptive findings revealed moderate concerns about costs and resources, data-driven challenges, data security and governance, legal and regulatory issues, legacy technology, and lack of standardized data. These results suggest that although respondents recognize the benefits of AI, they remain cautious about its implementation conditions. This is an important finding because AI-based auditing depends heavily on the quality, integrity, accessibility, and standardization of data. If audit data are fragmented, incomplete, non-standardized, or stored in legacy systems, even advanced algorithms may produce unreliable or insufficiently interpretable outputs. This finding is in line with research indicating that the integration of AI into auditing faces challenges related to data infrastructure, technological readiness, regulatory ambiguity, cost, and professional capability (12, 25, 26, 30). It also supports studies that emphasize the need to adapt accounting and audit education to the challenges of artificial intelligence, because the technical sophistication of AI systems must be matched by auditors' competence in interpreting, validating, and supervising algorithmic outputs (28).

The measurement model results confirmed the reliability and validity of the developed instrument. The overall Cronbach's alpha coefficient of 0.970 indicated excellent internal consistency, while the construct-level reliability indicators, composite reliability values, AVE indices, and Fornell–Larcker results confirmed adequate reliability, convergent validity, and discriminant validity. These findings show that the extracted qualitative themes were successfully transformed into measurable constructs and that the proposed model has an acceptable psychometric structure. From a methodological standpoint, this supports the value of combining qualitative thematic analysis with quantitative structural validation in developing models for emerging professional service technologies. This approach is compatible with grounded and exploratory studies that have sought to identify effective AI-related factors in improving audit processes and then organize them into conceptual or empirical frameworks (29). It also aligns with systematic and exploratory work emphasizing that AI adoption in auditing requires theory-building approaches capable of integrating technological, organizational, and professional dimensions (1, 4).

The structural model results showed that most hypothesized paths were statistically significant, confirming the internal coherence of the proposed model. The path from customer expectations of artificial intelligence to trust-building challenges in traditional auditing was strong and significant. This result suggests that as clients become more aware of AI capabilities, their expectations regarding accuracy, speed, transparency, traceability, and reliability increase; consequently, the limitations of traditional auditing become more visible. This finding is consistent with research in AI-enabled customer services showing that customer expectations are shaped by perceived service quality, responsiveness, trust, and usability (15, 20, 21). In auditing, this means that clients may no longer evaluate audit services only based on compliance with traditional standards, but also based on whether the audit process can provide timely, data-driven, and understandable assurance. Therefore, AI does not merely change audit procedures; it also changes the evaluative criteria through which clients judge audit quality and credibility.

The significant path from trust-building challenges in traditional auditing to technical sub-criteria for intelligent auditing indicates that weaknesses in traditional audit trust mechanisms can stimulate the need for technical solutions such as advanced analytics, learning algorithms, intelligent processing, data security, transparency, and interpretability. This finding supports previous research suggesting that AI applications in enterprise auditing can address some limitations of conventional audit methods by enabling automated analysis, broader transaction coverage, and enhanced risk identification (2, 3). However, the result also implies that technical sub-criteria must be developed in direct response to trust-related needs. In other words, AI tools should not be adopted simply because they are technologically advanced; they should be designed to solve specific trust deficits in audit services. This interpretation is consistent with the view that trust in AI auditing must be treated as a core element of professional practice rather than as a secondary feature of technology deployment (13).

One of the strongest structural effects in the model was the effect of technical sub-criteria for intelligent auditing on the key criteria for designing an artificial intelligence-oriented auditing model. This result confirms that the design of an effective AI-based audit model depends substantially on the quality of its technical foundations. Learning algorithms, intelligent processing and analysis, model accuracy, infrastructure, visualization, security, and interpretability are not peripheral components; they constitute the operational basis through which AI can generate reliable audit insights. This finding is aligned with studies emphasizing the role of cloud-based AI integration, advanced analytics, and algorithmic processing in improving audit performance (12, 32). It also supports evidence that the integration of AI and Industry 4.0 technologies is transforming accounting and auditing practices by shifting audit work toward data-intensive, technology-supported, and analytics-driven processes (5, 6).

The significant effect of the key criteria for designing an artificial intelligence-oriented auditing model on the benefits of AI in improving auditing services was another major result. This finding shows that the benefits of AI, including improved accuracy, reduced risk, broader coverage, better decision-making, and enhanced service quality, are realized when AI systems are guided by appropriate design criteria. Thus, the advantages of AI do not automatically emerge from the mere adoption of intelligent tools; rather, they depend on how those tools are designed, governed, interpreted, and integrated into audit workflows. This interpretation is supported by research showing that AI can improve financial auditing efficiency while also requiring ethical, regulatory, and professional safeguards (30, 31). It also corresponds with studies in financial and service contexts showing that AI-driven service benefits are mediated by service quality and moderated by customer trust (17, 22). Therefore, the present findings suggest that audit firms must move beyond technology acquisition and focus on model design quality as the mechanism that converts AI capability into audit value.

The path from strategies for ensuring the comprehensibility of and trust in outputs to the benefits of AI in improving auditing services was also significant. This finding confirms the centrality of explainability, documentation, visualization, review, and quality control in AI-based auditing. When clients and auditors can understand how AI-generated outputs are produced and how they should be interpreted, they are more likely to trust the service and perceive its benefits. This result is consistent with research on AI-mediated communication and conversational AI, which shows that trust formation is influenced by transparency, perceived competence, and the clarity of interaction between users and intelligent systems (18, 19). In audit services, this means that output transparency is not only a technical requirement but also a relational and managerial requirement. Explainable outputs can strengthen client confidence, reduce resistance, and support professional accountability.

The model also showed that strategies for increasing the acceptance of artificial intelligence had a strong significant effect on operational barriers to implementing the proposed model. This finding indicates that training, cultural development, gradual implementation, and organizational readiness are crucial for managing implementation challenges. It is consistent with research showing that AI adoption in financial service-oriented contexts is shaped by innovation climate, organizational support, and readiness for change (33). It also aligns with evidence from the banking and service sectors showing that customer experience and acceptance of AI-driven systems improve when users perceive the technology as useful, reliable, secure, and service-enhancing (23, 24). However, the direct path from strategies for increasing AI acceptance to the key criteria for designing the AI-oriented auditing model was not significant. This finding is theoretically important because it shows that acceptance strategies alone do not automatically improve model design. Instead, acceptance must be translated through operational preparation, infrastructure development, technical refinement, and governance mechanisms before it can influence the design quality of AI-based audit services.

The indirect effect results further clarified the mediating structure of the model. The strongest indirect effect was related to the pathway from technical sub-criteria for intelligent auditing through key design criteria to the benefits of AI in improving auditing services. This finding reinforces the idea that technical readiness influences audit service benefits primarily when it is embedded in a coherent model design. Other significant multistage pathways involving operational barriers, trust-building challenges, and technical sub-criteria demonstrate that AI-based auditing requires a systemic and staged implementation process. These findings are highly consistent with SEM-ANN evidence showing that the effect of AI-based audit services on client trust is complex and may involve both direct and nonlinear relationships among technical, service, and trust-related factors (32). The non-significant indirect pathway from AI acceptance strategies through design criteria to audit service benefits further confirms that trust and benefits cannot be achieved through acceptance rhetoric alone; they require technical competence, operational readiness, and explainable design.

The artificial neural network results complemented the structural equation modeling findings by identifying the most important predictors of the benefits of AI in auditing services. Advanced analytics had the highest normalized importance, followed by process transparency and reporting, model accuracy and quality, learning algorithms, intelligent processing and analysis, automation and visualization, interpretability and visualization, and data security and governance. This pattern shows that machine learning analysis prioritized analytical capability, transparency, model quality, and algorithmic reliability as the main drivers of AI-related audit benefits. These results are aligned with prior studies emphasizing that AI can enhance auditing by improving analytical depth, fraud detection, risk assessment, and decision support (10, 11, 27). They also reinforce the argument that intelligent auditing depends not merely on automation but on the ability to generate accurate, interpretable, and professionally meaningful insights. Overall, the convergence between SEM and ANN results strengthens the validity of the proposed model and demonstrates that both linear causal relationships and nonlinear predictive patterns support the central role of technical and trust-based design in AI-oriented auditing.

This study had several limitations that should be considered when interpreting the findings. First, although the mixed-method design strengthened the depth and validity of the results, the qualitative phase was based on interviews with 10 experts, and broader participation from regulators, audit committee members, software developers, and clients from different industries could have enriched the conceptual model. Second, the quantitative data were collected through self-report questionnaires, which may be influenced by perceptual bias, social desirability, and respondents' varying levels of familiarity with artificial intelligence. Third, the study was cross-sectional, and therefore it cannot fully capture how customer trust, AI acceptance, audit quality perceptions, and implementation barriers evolve over time. Fourth, although the ANN analysis improved predictive interpretation, it was based on the available survey variables and did not include actual operational audit data, system log data, or objective performance indicators from AI-based audit platforms.

Future studies should validate the proposed model in different institutional, regulatory, and industry contexts to examine whether the same structural relationships remain stable across audit firms, public-sector organizations, financial institutions, and technology-intensive companies. Longitudinal research is recommended to assess how trust in AI-based auditing develops after repeated use and whether initial resistance decreases as users gain experience with intelligent audit systems. Future researchers may also compare the perceptions of auditors, clients, regulators, audit committee members, and AI system developers to identify possible differences in expectations and trust mechanisms. In addition, experimental studies could examine how different levels of explainability, visualization, human oversight, and disclosure affect clients' confidence in AI-generated audit outputs. Finally, future models should incorporate objective technical indicators such as prediction accuracy, anomaly detection rates, processing time, false-positive rates, and audit cost reduction to complement perceptual data.

Audit firms and professional service organizations should approach artificial intelligence adoption as a comprehensive strategic transformation rather than a limited technological upgrade. Before implementing AI-based audit systems, organizations should assess data quality, digital infrastructure, staff readiness, cybersecurity capacity, legal compliance, and client expectations. Training programs should be designed to help auditors understand algorithmic outputs, evaluate model limitations, and preserve professional judgment in AI-supported audit environments. Audit firms should also provide clients with transparent explanations of how AI tools are used, what data are processed, how outputs are validated, and how human auditors supervise automated findings. Gradual implementation is recommended, beginning with low-risk analytical tasks and then expanding to more complex audit procedures as trust, competence, and governance capacity increase. Most importantly, AI-based auditing should be designed around accuracy, interpretability, accountability, and customer trust, because these elements determine whether intelligent audit services will be accepted and perceived as credible.

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## Authors' Contributions

All authors equally contributed to this study.

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The authors of this article declared no conflict of interest.

## Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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