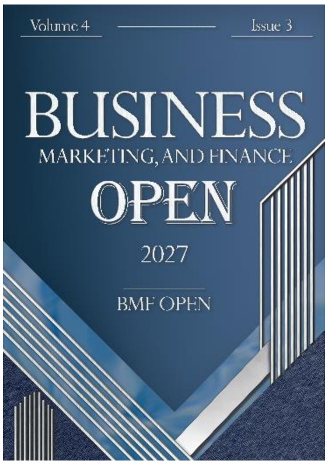
Presentation of an Artificial Intelligence-Based Auditing Services Model with an Emphasis on Customer Trust: Theme Analysis and Single-Layer Perceptron Neural Network

Toktam Javidi [1], Karim Nakhaei [2,*], Habibollah Nakhaei [3] and Mohammadreza Gholamzadeh [4]



Citation: Javidi, T., Nakhaei, K., Nakhaei, H., & Gholamzadeh, M. (2027). Presentation of an Artificial Intelligence-Based Auditing Services Model with an Emphasis on Customer Trust: Theme Analysis and Single-Layer Perceptron Neural Network. *Business, Marketing, and Finance Open*, 4(3), 1-13.

Received: 17 February 2026
Revised: 04 June 2026
Accepted: 13 June 2026
Initial Publication: 04 July 2026
Final Publication: 01 May 2027

[1] Department of Accounting, Bi.C., Islamic Azad University, Birjand, Iran;
[2] Department of Accounting, Bi.C., Islamic Azad University, Birjand, Iran;
[3] Department of Accounting, Bi.C., Islamic Azad University, Birjand, Iran;
[4] Department of Accounting, Bi.C., Islamic Azad University, Birjand, Iran;

* Correspondence: karimnakhaei@iau.ac.ir

Abstract: With the rapid expansion of artificial intelligence (AI) technologies in the auditing profession, traditional models of auditing service delivery have encountered new challenges regarding customer trust. Accordingly, the present study was conducted to develop an AI-based auditing services model centered on customer trust and to determine the relative importance of its constituent components and sub-themes, thereby addressing the requirements of digital transformation and the evolving expectations of clients concerning audit quality, transparency, and service reliability. This study is applied in terms of purpose and employs an exploratory mixed-methods (qualitative–quantitative) research design. In the qualitative phase, data were collected through 10 semi-structured interviews with experts in auditing and artificial intelligence using purposive and snowball sampling techniques and were analyzed through thematic analysis. In the quantitative phase, data were gathered from 358 auditors and audit service clients using a researcher-developed questionnaire consisting of 103 items across 27 sub-themes, measured on a five-point Likert scale. The results of the thematic analysis revealed that the AI-driven auditing services model possesses a multilayered structure encompassing traditional trust-building challenges, customer expectations, design criteria, technical requirements, and ultimate benefits. The findings from the single-layer perceptron neural network indicated that themes associated with advanced analytics, process transparency, and model accuracy possess the highest relative importance. Customer trust in AI-based auditing emerges from a complex interaction among technical, perceptual, and procedural dimensions and cannot be achieved solely through the implementation of technology. By integrating thematic analysis and artificial neural network techniques, this study provides an innovative framework for explaining and prioritizing trust-related components in AI-driven auditing services.

Keywords: Artificial Intelligence Auditing, Customer Trust, Thematic Analysis, Artificial Neural Network, Single-Layer Perceptron.

1. Introduction

The auditing profession has historically played a fundamental role in enhancing the credibility, transparency, and reliability of financial reporting. In increasingly complex business environments characterized by rapid technological change, globalization, and the exponential growth of digital data, traditional auditing approaches are facing unprecedented challenges. Organizations now generate massive volumes of structured and unstructured information that often exceed the analytical capabilities of conventional audit methodologies. As a result, auditors and accounting firms are increasingly compelled to adopt advanced technologies that can improve efficiency, effectiveness, and decision-making quality. Among these technologies, artificial intelligence (AI) has emerged as one of the most transformative innovations, reshaping the way auditing services are designed, delivered, and evaluated. Artificial intelligence encompasses a broad range of technologies, including machine learning, deep learning, natural language processing, robotic process automation, predictive analytics, and generative AI systems that enable organizations to automate complex cognitive tasks and derive actionable insights from large datasets [1-3]. The emergence of Industry 4.0 and the increasing digitalization of organizational processes have further accelerated the integration of AI into accounting and auditing practices, creating opportunities for more intelligent, data-driven, and proactive auditing systems [4, 5]. Consequently, auditing is evolving from a retrospective and sample-based activity toward a continuous, predictive, and technology-enabled assurance function that leverages advanced computational capabilities to identify risks, anomalies, and patterns more effectively than traditional approaches.

The growing adoption of artificial intelligence in auditing is driven by its potential to significantly improve audit quality and operational performance. AI technologies facilitate the analysis of large-scale datasets, enhance anomaly detection, automate repetitive procedures, and improve the precision and consistency of audit judgments. Research has shown that AI applications can contribute to greater audit effectiveness by enabling more comprehensive coverage of transactions, reducing human error, accelerating audit procedures, and supporting auditors in identifying complex risk patterns that may otherwise remain undetected [6-8]. Big data analytics, machine learning algorithms, and intelligent data processing systems have become increasingly important components of modern auditing environments because they allow auditors to extract valuable insights from extensive financial and operational data sources [9-11]. Similarly, robotic process automation has transformed numerous substantive audit procedures by automating routine tasks, improving efficiency, and allowing auditors to devote more time to higher-value analytical activities [12-14]. Furthermore, cloud-based AI solutions have expanded the accessibility and scalability of advanced auditing technologies, enabling organizations of various sizes to implement sophisticated audit analytics and decision-support systems [15]. These developments indicate that artificial intelligence is not merely a supplementary tool but is increasingly becoming a strategic enabler of innovation and transformation within the auditing profession.

Despite the substantial benefits associated with AI adoption, the implementation of artificial intelligence in auditing introduces a variety of challenges that extend beyond technical considerations. One of the most critical issues concerns customer trust. Auditing services derive much of their value from stakeholders' confidence in the reliability, objectivity, and integrity of audit outcomes. While AI systems may enhance analytical capabilities, their successful adoption depends largely on whether clients perceive these systems as trustworthy, transparent, and capable of producing reliable results. Trust has long been recognized as a central element in auditor-client relationships because it influences perceptions of audit quality, professional credibility, and long-term engagement outcomes [16, 17]. In the context of AI-driven auditing, trust becomes even more significant because stakeholders often have limited understanding of the algorithms, models, and decision-making mechanisms underlying intelligent systems. Consequently, concerns regarding transparency, explainability, accountability, data privacy, and ethical use of AI may create resistance among clients and reduce their willingness to rely on AI-generated audit outcomes [18, 19]. The challenge is therefore not simply to develop technologically advanced auditing systems but also to ensure that these systems inspire confidence among users and stakeholders.

Customer trust is closely connected to perceptions of audit quality and satisfaction. Prior research suggests that clients' satisfaction with auditing services significantly influences their evaluations of auditor performance and their intention to maintain professional relationships with auditors [20]. As AI becomes more integrated into auditing processes, customers increasingly expect improvements in service quality, responsiveness, transparency, and accuracy. However, these expectations must be balanced with concerns about algorithmic bias, lack of human judgment, and potential overreliance on automated systems. Auditors therefore face the challenge of integrating AI technologies while preserving the human elements of professional skepticism, ethical reasoning, and expert judgment that have traditionally underpinned audit credibility. Studies examining auditors' perceptions of AI indicate that while professionals generally recognize the positive contributions of AI to audit quality, they also emphasize the importance of maintaining human oversight and interpretability in intelligent auditing systems [21, 22]. Similarly, research on professional skepticism suggests that technological advancements should complement rather than replace auditors' critical thinking capabilities and professional expertise [23]. These findings highlight the need for a balanced approach that combines technological sophistication with mechanisms that enhance trust, accountability, and transparency.

Another important dimension of AI adoption in auditing relates to organizational readiness and digital transformation. The successful implementation of AI technologies depends on multiple factors, including technological infrastructure, organizational culture, auditor competencies, regulatory frameworks, and management support. Digital transformation in auditing requires not only technological investments but also significant changes in organizational processes, professional skills, and strategic priorities [24]. Auditors must acquire new competencies related to data analytics, machine learning, and technology governance to effectively utilize intelligent auditing systems. Research has demonstrated that auditor competence and information technology proficiency play a crucial role in achieving high-quality audit outcomes in digitally transformed environments [25]. Moreover, recent studies have emphasized that organizations often encounter barriers such as resistance to change, insufficient technical expertise, data quality issues, and concerns regarding regulatory compliance when implementing AI solutions [19, 26]. These challenges suggest that customer trust in AI-based auditing services is shaped not only by the technical performance of AI systems but also by broader organizational and environmental factors that influence the implementation process.

Recent developments in artificial intelligence have further expanded the scope of possibilities for auditing innovation. Advanced machine learning models, deep learning architectures, predictive analytics, and generative AI applications have introduced new opportunities for automating complex audit tasks and enhancing decision support capabilities [3, 27]. Deep learning techniques, in particular, have demonstrated considerable potential in identifying intricate patterns within large datasets and supporting more accurate risk assessments. Empirical evidence indicates that AI-based audit services can positively influence client trust when they provide reliable, transparent, and value-enhancing outcomes [28]. Similarly, studies examining the adoption of data analytics and artificial intelligence among audit professionals reveal that perceived usefulness, ease of use, organizational support, and trust-related factors significantly influence the willingness of auditors to embrace intelligent technologies [29]. The increasing convergence of AI, cloud computing, big data analytics, and intelligent automation is therefore creating a new paradigm in auditing in which technological capabilities and stakeholder trust become mutually reinforcing determinants of success.

Although previous studies have extensively examined the technological benefits, implementation challenges, ethical implications, and professional consequences of artificial intelligence in auditing, relatively limited attention has been devoted to developing an integrated framework that explains how customer trust is formed within AI-driven auditing services. Existing research has often focused on specific dimensions such as audit quality, professional perceptions, technological adoption, ethical considerations, or digital transformation [6, 18, 24]. However, customer trust is a multidimensional construct influenced by technical factors, organizational capabilities, process transparency, perceived reliability, and stakeholder expectations. Understanding the interactions among these dimensions is essential for designing AI-based auditing models that can achieve both technological effectiveness and stakeholder acceptance. Given the increasing strategic importance of artificial intelligence in auditing and the critical role of trust in determining the success of intelligent audit services, there is a clear need for a comprehensive framework that identifies the key trust-building factors and prioritizes their relative importance within an integrated model.

Therefore, the present study aims to develop an artificial intelligence-based auditing services model with an emphasis on customer trust and to identify and prioritize the key dimensions and sub-themes influencing trust formation through thematic analysis and artificial neural network techniques.

2. Methodology

This study is applied in terms of purpose and exploratory mixed-methods (qualitative–quantitative) in terms of research design. In the qualitative phase, the target population consisted of auditing experts, university faculty members, and artificial intelligence specialists. Participants were selected through purposive and snowball sampling methods, and data were collected through 10 semi-structured interviews, which continued until theoretical saturation was achieved. The data collection instrument was an interview protocol whose questions focused on the challenges of gaining customer trust in auditing firms, the role of artificial intelligence in improving audit service quality, customers' expectations regarding the adoption of this technology, design criteria for an AI-based auditing model (including accuracy, transparency, interpretability, data security, and execution speed), critical technical sub-criteria (such as machine learning algorithms and natural language processing), implementation barriers, and strategies for enhancing AI acceptance. Qualitative data were analyzed using thematic analysis through the stages of initial, axial, and final coding. The validity of the findings was confirmed through expert review and inter-coder agreement. The outcome of this phase was the extraction of the main themes and sub-themes associated with AI-based auditing services and customer trust.

In the quantitative phase, the statistical population consisted of professional auditors employed in auditing firms and clients of auditing services (financial managers and senior accountants of companies). Due to the nature of the population, it was considered unlimited. Sampling was conducted using cluster and convenience sampling methods. Based on Cochran's formula, 358 valid questionnaires were obtained and used for the final analysis. The data collection instrument was a researcher-developed questionnaire designed based on the themes extracted from the qualitative phase. The variables were operationalized into measurable items, resulting in 103 items representing 27 sub-themes. Responses were measured using a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." The content validity of the questionnaire was confirmed by experts, and its reliability was verified using Cronbach's alpha coefficient. To analyze the data and determine the importance and priority of sub-themes in explaining customer trust, Artificial Neural Networks (ANNs) with a Single-Layer Perceptron (SLP) architecture were employed. Finally, by integrating the findings of the qualitative and quantitative phases, a comprehensive AI-based auditing services model with a focus on customer trust was developed.

3. Findings and Results

The interview participants consisted of 10 specialists in accounting, auditing, financial management, and related technologies who were selected based on their expertise and professional experience. These individuals were drawn from diverse environments, including universities, auditing firms, manufacturing and service companies, and governmental organizations, to ensure the collection of comprehensive and multidimensional perspectives. The average age of the participants was approximately 45 years, ranging from 36 to 58 years. In terms of educational qualifications, the majority (6 participants) held doctoral degrees, while 4 held master's degrees. Their areas of specialization primarily focused on auditing, financial management, information systems, and artificial intelligence. Table 1 presents the demographic characteristics of the experts.

Table 1. Demographic Characteristics of the Experts

No.	Age (Years)	Education	Workplace	Academic Rank/Position	Specialization
1	45	PhD in Accounting	Islamic Azad University	Assistant Professor / Faculty Member	Auditing
2	38	M.A. in Accounting	Private Manufacturing and Service Company	Chief Financial Officer	Accounting and Financial Management
3	54	PhD in Financial Management	Public University	Associate Professor / Faculty Member	Financial Management and Auditing
4	45	M.A. in Accounting	Private Auditing Firm	Senior Information Technology Manager	Information Systems and Financial Technology
5	58	PhD in Accounting	Large Private Auditing Firm	Chief Executive Officer	Auditing and Risk Management
6	50	PhD in Accounting	National Audit Organization (Government)	Director General of Supervision and Auditing	Government Auditing and Risk Management
7	52	PhD in Accounting	Independent Private Auditing Firm	Senior Auditor and Independent Consultant	Financial Auditing and Risk Management
8	36	PhD Candidate in Accounting	Islamic Azad University, Research and Auditing Unit	Researcher and Assistant Lecturer	Intelligent Auditing, AI in Financial Services
9	45	M.A. in Financial Management / MBA in Data Analytics	FinTech Consulting Company	Senior Technology and Data Analytics Consultant	Financial Data Analytics, AI in Auditing Services and Risk Management
10	42	M.A. in Financial Management	Medium-Sized Industrial Company	Financial Manager	Financial Management, Internal Control, Financial Reporting

In the present study, the final organization of themes was structured in a manner that enabled the extraction of a comprehensive model for AI-based auditing services with a particular emphasis on customer trust. The conceptual model developed at the conclusion of the study illustrates the relationships among a set of key elements, including trust-building challenges in traditional auditing, the role and benefits of artificial intelligence, customer expectations, technical criteria and sub-criteria, trust assurance mechanisms, operational barriers, and strategies for enhancing acceptance. This model provides a coherent framework for evaluating and assessing the proposed model and serves as a foundation for the development, implementation, and analysis of intelligent auditing services.

Table 2. Main Themes and Their Definitions

Main Theme	Definition
Trust-Building Challenges in Traditional Auditing Services	Problems and barriers that reduce customer trust in traditional auditing services, including insufficient transparency, inconsistent quality, technological limitations, and communication challenges.
Customer Expectations of Artificial Intelligence in Auditing	Customer expectations and requirements regarding accuracy, speed, transparency, and traceability in AI-based auditing services.
Benefits of Artificial Intelligence in Improving Auditing Services	Positive aspects and added value of AI in enhancing the accuracy, quality, coverage, and efficiency of auditing services.
Key Design Criteria for an AI-Driven Auditing Model	Key indicators and criteria used for designing and evaluating an AI-based auditing model.
Technical Sub-Criteria for Intelligent Auditing	Technical details and algorithmic and software infrastructures required for successful intelligent auditing implementation.
Strategies for Ensuring Interpretability and Trustworthiness of Outputs	Methods and measures aimed at increasing transparency and confidence in outputs generated by AI systems.
Operational Barriers to Implementing the Proposed Model	Limitations and operational challenges that may hinder the successful implementation of intelligent auditing systems.
Strategies for Enhancing AI Acceptance	Activities and recommendations aimed at improving the acceptance and effective use of artificial intelligence within organizations.

In this section, descriptive statistics, including mean, standard deviation, skewness, and kurtosis, were examined for all sub-themes. The results are presented in the descriptive statistics table. Based on the findings, all sub-themes had an identical sample size (358 valid observations), and their variation ranges were consistent with the five-point Likert scale and the aggregation of questionnaire items. Within the deep learning framework, sub-themes related to AI expectations, process transparency and reporting, advanced analytics, automation and visualization, learning algorithms, and intelligent processing and analytics were considered the primary inputs to the neural network.

Table 3. Descriptive Statistics of the Sub-Themes

Sub-Themes	Mean	Maximum	Minimum	Standard Deviation
Process Transparency and Reporting	20.66	25	11	2.844
Inequality and Inconsistent 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
Preservation of 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 Analytics	15.94	20	10	2.574
Infrastructure and Tools	16.12	20	7	2.447
Interpretability and Visualization Capability	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
Cost 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 Sample Size	358	—	—	—

On the other hand, sub-themes related to implementation challenges and barriers, including "Structural and Communication Challenges," "Data-Driven Challenges," "Cost and Resources," "Legacy Technology," and "Lack of Standardized Data," also exhibited substantial variability. In the next stage, the descriptive data were used as inputs for the artificial neural network to identify hidden patterns among technical, organizational, and perceptual sub-themes and the study's ultimate outcome, namely the benefits of artificial intelligence in improving auditing services. The relatively high mean values for variables such as "Quality and Accuracy Improvement," "Expansion of Scope and Coverage," and "Model Accuracy and Quality" indicate that the neural network's expected output is strongly supported by empirical evidence in the data and that the relationships between inputs and outputs are not merely linear and straightforward.

Table 4. 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 Analytics	0.112	79
6	Automation and Visualization	0.106	75
7	Interpretability and Visualization Capability	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	Preservation of 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	Cost and Resources	0.047	33
20	Culture and Organization	0.044	31
21	Legal and Regulatory Issues	0.041	29
22	Inequality and Inconsistent 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 presented in Table 4 indicate that the artificial neural network assigned the greatest weight and importance to sub-themes associated with analytical capabilities, transparency, and the quality of artificial intelligence models. The variable "Advanced Analytics," with the highest normalized importance (100%), was identified as the most influential factor in predicting the benefits of artificial intelligence in auditing services. This finding suggests that, from a machine learning perspective, the capability to perform complex analyses and extract advanced patterns plays a central role in generating value within intelligent auditing. Likewise, variables such as "Process Transparency and Reporting," "Model Accuracy and Quality," and "Learning Algorithms" ranked among the most important factors, highlighting the significance of trustworthiness, result accuracy, and algorithmic structure in the performance of AI-based auditing systems. Conversely, variables such as “Legacy Technology,” “Lack of Standardized Data,” and “Structural and Communication Challenges” demonstrated relatively lower importance, indicating that these factors primarily function as indirect barriers whose effects are mediated through technical and model-design variables within the neural network. Overall, these findings demonstrate that machine learning, through its ability to identify nonlinear patterns, emphasizes the pivotal role of technical and analytical components in the success of AI-driven auditing.

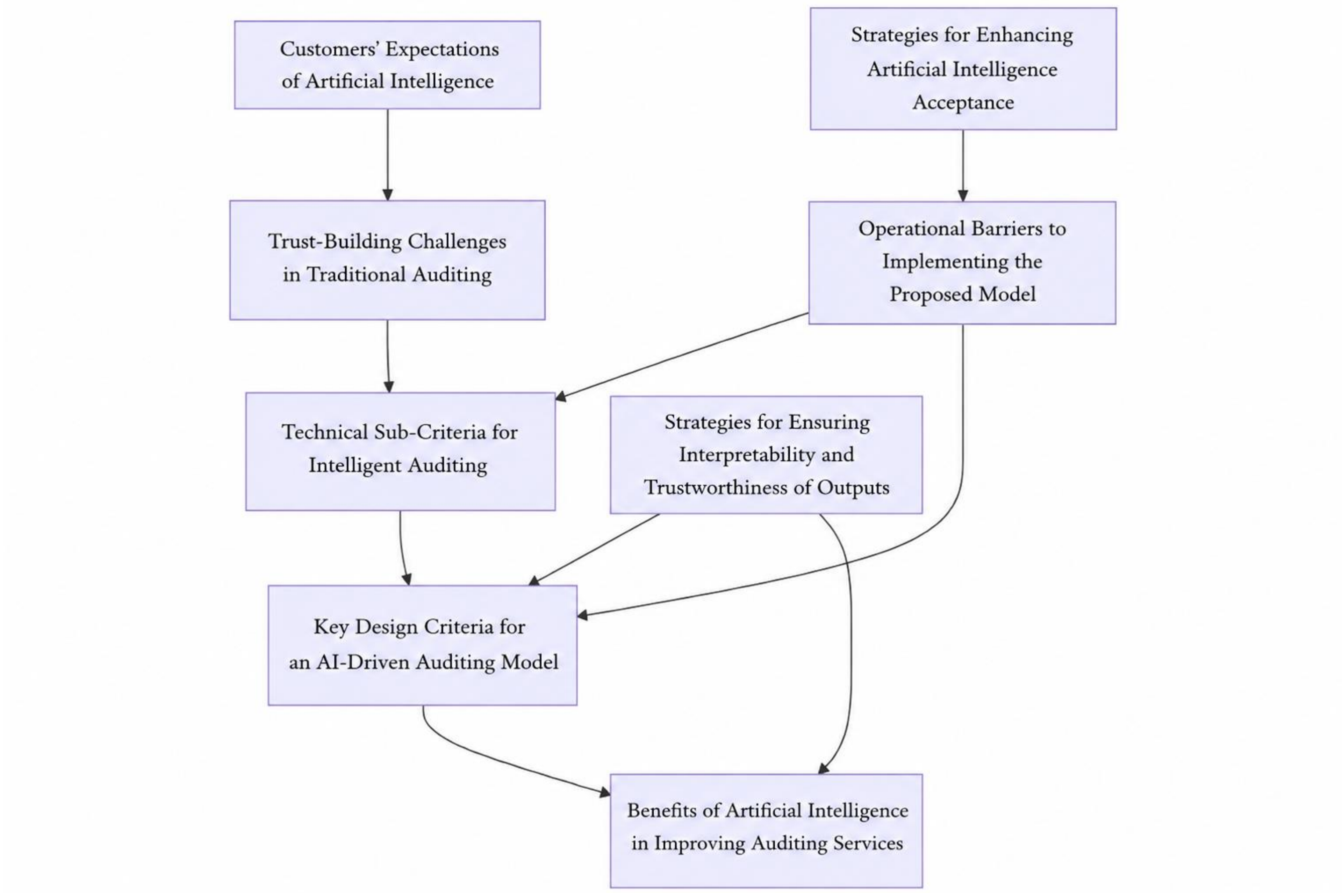


Figure 1. Final Model of the Study

4. Discussion and Conclusion

The purpose of the present study was to develop an artificial intelligence-based auditing services model with an emphasis on customer trust and to determine the relative importance of the factors influencing trust formation through thematic analysis and artificial neural network techniques. The findings of the qualitative phase revealed that customer trust in AI-driven auditing services is a multidimensional phenomenon shaped by a network of interrelated factors, including trust-building challenges in traditional auditing, customer expectations of artificial intelligence, technical sub-criteria for intelligent auditing, key design criteria, mechanisms for ensuring trustworthiness and interpretability, operational barriers, and strategies for enhancing AI acceptance. The results indicate that customer trust cannot be viewed merely as an outcome of technological implementation; rather, it emerges through the interaction of technological, organizational, behavioral, and perceptual dimensions. This finding is consistent with previous research emphasizing that the successful adoption of AI in auditing requires more than technological capability and depends on broader contextual and stakeholder-related factors [19, 24, 26].

The identified thematic structure suggests that trust in AI-based auditing develops through a process in which technical excellence, transparency, organizational readiness, and user acceptance collectively influence stakeholders' perceptions of reliability and value.

One of the most important findings of the study was the identification of customer expectations as a fundamental component of AI-driven auditing services. The qualitative results showed that customers increasingly expect auditing systems to provide greater accuracy, speed, transparency, traceability, and consistency than traditional audit methods. These expectations reflect broader transformations occurring across digital business environments where stakeholders seek real-time insights and evidence-based decision support. This finding aligns with previous studies suggesting that artificial intelligence enhances the capability of auditing systems to process large datasets, detect anomalies, and improve service quality [4, 6, 7]. Furthermore, research on AI adoption in accounting and auditing indicates that users generally perceive intelligent systems as valuable when they improve efficiency and reduce uncertainty in decision-making processes [21, 22]. Therefore, customer expectations represent not only desired service outcomes but also a benchmark against which the effectiveness and trustworthiness of AI-based auditing services are evaluated.

The findings also revealed that trust-building challenges inherited from traditional auditing remain relevant in technology-enabled environments. Themes such as inconsistent audit quality, communication barriers, and limitations in transparency emerged as important antecedents influencing the adoption of AI-based auditing services. This result suggests that artificial intelligence does not automatically eliminate existing trust deficiencies but instead operates within pre-existing relational and organizational contexts. Trust has long been recognized as a critical factor in auditor-client relationships, influencing perceptions of credibility, professional competence, and audit quality [16, 17]. The present findings support this perspective by demonstrating that the effectiveness of AI technologies is partly dependent on their ability to address longstanding concerns regarding reliability and transparency. Consequently, organizations that seek to implement AI-driven auditing systems must recognize that technological innovation alone cannot compensate for deficiencies in communication, governance, or stakeholder engagement.

Another significant finding relates to the central role of technical sub-criteria in intelligent auditing systems. The thematic analysis identified machine learning algorithms, intelligent data processing, advanced analytics, automation capabilities, data governance, and infrastructure readiness as key technical dimensions supporting AI-based auditing. The neural network results further reinforced this conclusion by assigning the highest relative importance to advanced analytics, process transparency and reporting, model accuracy and quality, learning algorithms, and intelligent processing capabilities. These findings suggest that customers perceive value primarily through the analytical strength and technical reliability of AI systems. The prominence of advanced analytics as the most influential predictor of perceived benefits is particularly noteworthy because it highlights the importance of extracting meaningful insights from large and complex datasets. This finding is highly consistent with research emphasizing the transformative role of machine learning, big data analytics, and predictive modeling in modern auditing practices [9-11]. Similarly, studies have demonstrated that artificial intelligence enhances auditors' ability to identify patterns, anomalies, and risk indicators that may not be detectable through traditional approaches [1, 27]. The present results therefore provide empirical support for the proposition that analytical capability represents one of the most important sources of value creation in intelligent auditing.

The high importance assigned to process transparency and reporting also carries significant theoretical and practical implications. Transparency emerged as both a customer expectation and a determinant of trust, suggesting that stakeholders are not satisfied merely with accurate results but also seek understanding of how those results are generated. The growing complexity of AI models often creates “black box” concerns in which users are unable to interpret or evaluate algorithmic decision-making processes. The findings of this study indicate that trust increases when auditing systems provide transparent procedures, explainable outputs, and clear reporting mechanisms. This conclusion is consistent with research highlighting the ethical and governance challenges associated with artificial intelligence adoption in auditing [18]. It also supports evidence suggesting that users are more likely to accept AI-generated recommendations when the underlying logic and decision pathways are understandable and auditable [28]. Therefore, explainability and transparency should be regarded not merely as technical characteristics but as strategic trust-building mechanisms.

The neural network analysis further demonstrated that model accuracy and learning algorithms are among the most influential determinants of perceived benefits. These findings indicate that customers and auditors place considerable importance on the reliability and predictive capability of AI systems. From a theoretical perspective, this result reflects the fundamental economic value of artificial intelligence as a prediction technology capable of reducing uncertainty and improving decision quality [1]. Prior research has consistently emphasized that AI systems can contribute to audit quality when they generate accurate, consistent, and evidence-based conclusions [6, 21]. The present findings extend this literature by demonstrating that perceptions of accuracy and model quality directly influence trust formation. Consequently, organizations seeking to implement AI-driven auditing systems must prioritize rigorous model validation, continuous performance monitoring, and algorithmic improvement to maintain stakeholder confidence.

An additional contribution of the study is the identification of interpretability, visualization capability, and preservation of the human role as important components of trust. Although technical variables received the highest importance scores, factors related to human oversight and interpretability remained significant. This finding supports the argument that artificial intelligence should augment rather than replace professional judgment. Previous studies have suggested that auditors’ skepticism, ethical reasoning, and professional expertise remain indispensable even in highly automated environments [16, 23]. Similarly, research on digital transformation has emphasized that successful technological adoption depends on the effective integration of human and machine capabilities [24]. The present results reinforce these conclusions by indicating that trust is enhanced when AI systems operate within a framework that preserves human accountability and professional oversight.

The findings related to operational barriers also provide valuable insights. Variables such as data-driven challenges, implementation costs, legal and regulatory issues, organizational culture, legacy technologies, and shortages of standardized data were identified as obstacles to successful implementation. Although these variables received lower relative importance scores in the neural network analysis, this does not imply that they are unimportant. Rather, their effects appear to be indirect, influencing trust and perceived benefits through their impact on technical performance and implementation quality. This interpretation is consistent with studies emphasizing that organizational readiness, technological infrastructure, and regulatory compliance represent essential conditions for successful AI adoption [15, 19, 25]. Furthermore, recent investigations into AI adoption among audit professionals have shown that barriers related to organizational support, technological maturity, and user readiness can significantly affect implementation outcomes [29]. Therefore, organizations must address these contextual challenges to maximize the effectiveness of intelligent auditing systems.

The study also highlighted the importance of training, cultural development, and gradual implementation strategies. These findings suggest that acceptance of AI-based auditing services is a dynamic process that requires continuous learning and adaptation. The transition from traditional auditing to intelligent auditing involves significant changes in professional roles, organizational routines, and stakeholder expectations. Research on business model transformation and digital innovation similarly emphasizes that technological change is most successful when accompanied by investments in human capital and organizational learning [5]. The findings of this study therefore indicate that customer trust is strengthened when organizations actively promote education, awareness, and stakeholder engagement throughout the implementation process.

Overall, the results demonstrate that customer trust in AI-based auditing services emerges from a complex interplay of technical excellence, transparency, organizational readiness, human oversight, and stakeholder acceptance. The integration of thematic analysis and artificial neural networks enabled the identification not only of the relevant dimensions but also of their relative importance within a comprehensive conceptual framework. The findings contribute to the growing literature on intelligent auditing by providing empirical evidence that trust is shaped by both technological and social factors and that the success of AI-driven auditing depends on achieving a balance between analytical capability, transparency, interpretability, and human involvement. As artificial intelligence continues to transform the auditing profession, organizations that effectively address these dimensions will be better positioned to realize the benefits of intelligent auditing while maintaining stakeholder confidence and trust.

The present study should be interpreted in light of several limitations. First, the qualitative phase relied on a relatively limited number of experts, which may restrict the diversity of perspectives represented in the thematic framework. Second, the quantitative phase was conducted within a specific professional context, and the findings may not be fully generalizable to all auditing environments or countries with different regulatory and technological conditions. Third, the study focused on perceptions of trust and the relative importance of factors influencing trust formation rather than measuring actual behavioral outcomes associated with AI adoption. Finally, although the neural network approach provided valuable insights into variable importance, the cross-sectional nature of the data limits the ability to draw conclusions regarding causal relationships among the identified constructs.

Future studies may examine the proposed model in different cultural, regulatory, and industrial contexts to assess its generalizability and robustness. Longitudinal research designs could provide deeper insights into how customer trust evolves over time as organizations gain experience with AI-based auditing systems. Researchers may also investigate the moderating effects of demographic characteristics, technological literacy, organizational size, and industry type on trust formation. Comparative studies between traditional auditing approaches and AI-driven auditing systems could further clarify the mechanisms through which trust is established. Additionally, future research could employ more advanced deep learning architectures and hybrid analytical techniques to explore complex nonlinear relationships among trust-related variables.

Organizations seeking to implement AI-based auditing services should prioritize transparency, explainability, and communication throughout the auditing process. Investment in advanced analytics, robust data governance frameworks, and high-quality machine learning models is essential for maximizing the perceived value of intelligent auditing systems. Auditing firms should also develop comprehensive training programs to enhance employees' technological competencies and reduce resistance to innovation. Maintaining appropriate human oversight over AI-generated outputs can strengthen accountability and improve stakeholder confidence. Finally, a gradual implementation strategy that combines technological deployment with cultural adaptation and stakeholder engagement is likely to increase acceptance and foster sustainable trust in AI-driven auditing services.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

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

References

[1] A. Agrawal, J. Gans, and A. Goldfarb, *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Press (in English), 2018.

[2] T. H. Davenport, *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*. MIT Press (in English), 2018.

[3] T. H. Davenport and N. Mittal, "How Generative AI Is Changing Creative Work," (in English), 2022. [Online]. Available: https://hbr.org/2022/11/how-generative-ai-is-changing-creative-work.

[4] S. Daris and E. Moghadamnia, "The Impact of Artificial Intelligence and Industry 4.0 on Changes in Accounting and Auditing Practices," in *Proceedings of the 8th International Conference on Management, Accounting and Economics in Sustainable Development*, Mashhad, 2024.

[5] D. Samson, A. Ellis, and S. Black, *Business Model Transformation: The AI & Cloud Technology Revolution*. Routledge (in English), 2023.

[6] I. O. Adeoye, R. I. Akintoye, A. Theophilus, and T. Aguguom, "Artificial Intelligence and Audit Quality: Implications for Practicing Accountants," (in English), *Asian Economic and Financial Review,* vol. 13, no. 11, pp. 756-772, 2023, doi: 10.55493/5002.v13i11.4861.

[7] A. Rizk, "The Contribution of Artificial Intelligence Technologies in Supporting the Quality of Professional Performance of Accounting and Auditing Firms in Egypt: Empirical Study on Large Accounting and Auditing Firms," (in English), *Accounting Thought,* vol. 24, no. 2, pp. 480-563, 2020.

[8] F. Sarraf and A. Farhangian, "Application of Artificial Intelligence in Accounting," (in English), *Journal of New Research Approaches in Management and Accounting,* vol. 6, no. 86, pp. 108-124, 2022.

[9] G. Salijeni, A. Samsonova-Taddei, and S. Turley, "Big Data and Changes in Audit Technology: Contemplating a Research Agenda," (in English), *Accounting and Business Research,* vol. 49, no. 1, pp. 95-119, 2019, doi: 10.1080/00014788.2018.1459458.

[10] A. F. Hayek, "Data Science and External Audit," in *Sustainable Development through Data Analytics and Innovation*: Springer, 2022, pp. 45-62.

[11] S. Naghdi, A. Fazlzadeh, V. Ahmadian, and M. Abbas Mohsen Al-Tiyawi, "Big Data Analytics in Auditing Using Artificial Intelligence and Machine Learning Techniques," in *Proceedings of the 3rd International Conference on Economics and Business Management*, Tehran, 2024.

[12] K. C. Moffitt, A. M. Rozario, and M. Vasarhelyi, "Robotic Process Automation for Auditing," (in English), *Journal of Emerging Technologies in Accounting,* vol. 15, no. 1, pp. 1-10, 2018, doi: 10.2308/jeta-10589.

[13] M. Cohen, A. M. Rozario, and C. A. Zhang, "Exploring the Use of Robotic Process Automation (RPA) in Substantive Audit Procedures," (in English), 2019. [Online]. Available: https://www.cpajournal.com/2019/08/14/exploring-the-use-of-robotic-process-automation-rpa-in-substantive-audit-procedures/.

[14] L. A. Cooper, D. K. Holderness, Jr., T. L. Sorensen, and D. A. Wood, "Robotic Process Automation in Public Accounting," (in English), *Accounting Horizons,* vol. 33, no. 4, pp. 15-35, 2019, doi: 10.2308/acch-52466.

[15] Y. A. A. Huson, L. S. Garcia, M. A. G. Benau, and N. M. Aljawarneh, "Empirical Investigation into the Integration of Cloud-Based Artificial Intelligence in Auditing," in *PressAcademia Procedia (PAP)*, 2023, vol. 18, pp. 113-114, doi: 10.17261/Pressacademia.2023.1874.

[16] E. Aschauer, M. Fink, A. Moro, K. van Bakel-Auer, and B. Warming-Rasmussen, "Trust and Professional Skepticism in the Relationship between Auditors and Clients: Overcoming the Dichotomy Myth," (in English), *Behavioral Research in Accounting,* vol. 29, no. 1, pp. 19-42, 2017, doi: 10.2308/bria-51654.

[17] W. A. Kerler and L. N. Killough, "The Effects of Satisfaction with a Client's Management during a Prior Audit Engagement, Trust, and Moral Reasoning on Auditors' Perceived Risk of Management Fraud," (in English), *Journal of Business Ethics,* vol. 85, pp. 109-136, 2009, doi: 10.1007/s10551-008-9752-x.

[18] I. Munoko, H. L. Brown-Liburd, and M. Vasarhelyi, "The Ethical Implications of Using Artificial Intelligence in Auditing," (in English), *Journal of Business Ethics,* vol. 167, no. 2, pp. 209-234, 2020, doi: 10.1007/s10551-019-04407-1.

[19] P. Hamzah, E. Yeba, S. P. Maithy, and G. B. Poetra, "Opportunities and Challenges in Integrating Artificial Intelligence into Financial Auditing," (in English), *Journal of Economic Education and Entrepreneurship Studies,* vol. 5, no. 4, pp. 591-600, 2024, doi: 10.62794/je3s.v5i4.4563.

[20] Z. M. Ali, R. Mail, and S. M. Amirul, "The Mediation Effect of Clients' Satisfaction between Audit Quality and Auditor Retention of Small and Medium Enterprises (SMEs)," (in English), *International Journal of Accounting,* vol. 4, no. 17, pp. 53-65, 2019.

[21] I. Albawwat and Y. Frijat, "An Analysis of Auditors' Perceptions towards Artificial Intelligence and Its Contribution to Audit Quality," (in English), *Accounting,* vol. 7, pp. 755-762, 2021, doi: 10.5267/j.ac.2021.2.009.

[22] N. Narimani and M. Hemmatfar, "Analysis of Auditors' Perceptions of Artificial Intelligence and Its Contribution to Audit Quality," (in English), *Nokhbegan-e Olum va Mohandesi Journal,* vol. 9, no. 2, pp. 1-15, 2024.

[23] G. Puthukulam, A. Ravikumar, R. V. K. Sharma, and K. M. Meesaala, "Auditors' Perception on the Impact of Artificial Intelligence on Professional Skepticism and Judgment in Oman," (in English), *Universal Journal of Accounting and Finance,* vol. 9, pp. 1184-1190, 2021, doi: 10.13189/ujaf.2021.090527.

[24] D. Barr-Pulliam, H. L. Brown-Liburd, and I. Munoko, "The Effects of Person-Specific, Task, and Environmental Factors on Digital Transformation and Innovation in Auditing: A Review of the Literature," (in English), *Journal of International Financial Management and Accounting,* vol. 33, no. 2, pp. 337-374, 2022, doi: 10.1111/jifm.12148.

[25] S. Samukri, R. Saleh, and A. E. Syafitri, "Auditor Competence and the Use of Information Technology in Produce Quality Audits in the Era of the Industrial Revolution 4.0: Study on Auditors at KAP South Jakarta, Indonesia," (in English), *IRE Journals,* vol. 5, no. 11, pp. 13-21, 2022.

[26] F. Sharafi and M. Badri, "Identifying and Examining the Role of Artificial Intelligence Factors in Improving the Auditing Process: Grounded Theory Approach," in *Proceedings of the 1st Conference on Humanities with a Modern Approach*, Astara, 2024.

[27] I. Haq, M. Abatemarco, and J. Hoops, "The Development of Machine Learning and Its Implications for Public Accounting," (in English), 2020. [Online]. Available: https://www.cpajournal.com/2020/07/10/the-development-of-machine-learning-and-its-implications-for-public-accounting/.

[28] A. Rawashdeh, "A Deep Learning-Based SEM-ANN Analysis of the Impact of AI-Based Audit Services on Client Trust," (in English), *Journal of Applied Accounting Research,* 2023, doi: 10.1108/JAAR-10-2022-0273.

[29] M. Torroba, J. R. Sánchez, L. López, and Á. Callejón, "Investigating the Impacting Factors for Audit Professionals to Adopt Data Analysis and Artificial Intelligence: Empirical Evidence from Spain," (in English), *International Journal of Accounting Information Systems,* vol. 56, p. 100738, 2025, doi: 10.1016/j.accinf.2025.100738.