Developing a Model for the Application of Advanced Technologies and Automation in the Auditing Profession

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Abstract: This study aimed to develop and validate an integrated model for the application of advanced technologies and automation in the auditing profession by examining technological, organizational, professional, regulatory, and implementation factors and their effects on audit process transformation and audit outcomes. The study employed an exploratory mixed-methods design. In the qualitative phase, 18 experts in auditing, accounting information systems, digital transformation, and advanced audit technologies were selected through purposive sampling and interviewed using in-depth semi-structured interviews until theoretical saturation was achieved. The interview data were coded and organized into dimensions, components, and indicators. Based on the qualitative findings, a structured questionnaire was developed and distributed among auditing and accounting professionals. Of 312 distributed questionnaires, 286 valid responses were analyzed. The measurement model was evaluated using Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity, while the structural model was assessed using path coefficients, t statistics, coefficients of determination, predictive relevance, effect sizes, and model-fit indices. Technological infrastructure significantly affected advanced audit technologies ($\beta = 0.286$, $p < 0.001$), as did organizational readiness ($\beta = 0.241$, $p < 0.001$), auditor digital competencies ($\beta = 0.319$, $p < 0.001$), and regulatory and ethical governance ($\beta = 0.174$, $p = 0.001$), whereas implementation barriers and risks had a significant negative effect ($\beta = -0.168$, $p = 0.002$). Advanced audit technologies strongly predicted audit process transformation ($\beta = 0.604$, $p < 0.001$), and audit process transformation significantly predicted audit outcomes ($\beta = 0.571$, $p < 0.001$). Advanced audit technologies also directly affected audit outcomes ($\beta = 0.226$, $p < 0.001$). The model explained 58.7% of the variance in advanced audit technologies, 67.1% in audit process transformation, and 63.8% in audit outcomes. The findings indicate that successful integration of advanced technologies and automation in auditing depends on coordinated development of technological infrastructure, organizational readiness, auditor digital competencies, and regulatory governance, while minimizing implementation barriers. Audit process transformation represents the principal mechanism through which technological adoption improves audit quality, efficiency, accuracy, and professional performance.

Keywords: Advanced Technologies, Automation, Auditing Profession, Artificial Intelligence, Robotic Process Automation, Audit Process Transformation, Audit Outcomes.

1. Introduction

The auditing profession is undergoing a profound transformation as advanced technologies increasingly reshape the way financial information is produced, processed, examined, and interpreted. For decades, auditing relied predominantly on manual procedures, sample-based testing, documentary examination, professional judgment, and retrospective evaluation of financial transactions. However, the accelerating digitalization of organizations, the rapid growth of data volumes, and the increasing complexity of business processes have created an environment in which conventional audit approaches alone are often insufficient for providing timely, comprehensive, and high-

quality assurance. Technologies such as artificial intelligence, robotic process automation, machine learning, advanced data analytics, cloud computing, blockchain, and generative artificial intelligence have gradually become integrated into auditing and accounting activities, altering both the technical infrastructure of audit work and the competencies expected of auditors. The development of such technologies has shifted attention from whether auditing should become technologically enabled toward how advanced technologies can be systematically integrated into audit processes in a manner that improves quality, efficiency, professional judgment, risk assessment, and organizational adaptability [1, 2].

Digital transformation has particularly important implications for auditing because audit activities involve large volumes of structured and unstructured data, repetitive procedures, rule-based verification, anomaly identification, and professional evaluation. Many of these tasks are increasingly amenable to automation. Robotic process automation, for example, can perform highly repetitive and standardized activities such as extracting data from accounting systems, reconciling balances, transferring information across applications, generating routine audit documentation, and conducting predefined control tests. By transferring such activities from human auditors to software robots, audit teams can devote greater attention to complex risk assessments, professional skepticism, interpretation of unusual transactions, and judgment-intensive areas. Research on RPA has therefore emphasized its potential to improve audit productivity, reduce processing time, increase consistency, and minimize human error in routine audit procedures [3, 4]. At the same time, the effective application of automation requires careful identification of tasks that are sufficiently structured, rule-based, repetitive, and stable to justify automation. A structured framework for RPA implementation is therefore necessary to ensure that automation is introduced where it creates genuine audit value rather than merely transferring inefficient procedures into digital form [5].

The relationship between automation and audit quality is particularly significant. Audit quality depends on the auditor's ability to obtain sufficient and appropriate evidence, identify material misstatements, assess risk accurately, apply professional skepticism, and communicate conclusions effectively. Automated systems can enhance some of these functions by processing substantially larger datasets than would be feasible through manual examination, executing procedures consistently, identifying exceptional patterns, and supporting continuous monitoring. RPA may also reduce the risk of clerical errors and increase the reproducibility of audit procedures when appropriate controls are designed around automated processes. Empirical and conceptual studies have therefore increasingly examined the capacity of automation to enhance audit quality and strengthen the reliability of audit processes [6, 7]. Nevertheless, the relationship between automation and audit quality is not necessarily automatic or uniformly positive. Poorly designed automation, inadequate supervision, insufficient technological knowledge, weak governance, or inappropriate reliance on automated outputs may introduce new sources of audit risk. Consequently, the quality implications of automation depend on the interaction between technological capabilities, organizational controls, auditor competence, and the design of audit procedures.

Artificial intelligence extends the transformation of auditing beyond the automation of routine processes. Whereas RPA primarily automates repetitive, rule-based activities, artificial intelligence enables systems to identify patterns, classify information, generate predictions, analyze anomalies, and support more complex forms of decision-making. In auditing, AI can be used for fraud detection, risk assessment, anomaly identification, contract analysis, transaction classification, going-concern evaluation, and prioritization of areas requiring additional auditor attention. Systematic examinations of AI and automation in accounting and auditing indicate that both technologies are increasingly converging, with automation handling standardized processes and AI providing analytical and cognitive capabilities that can augment professional judgment [1, 8]. This convergence suggests that

future audit systems will be characterized not by a single technology but by interconnected technological ecosystems in which software robots, predictive algorithms, machine learning models, data analytics platforms, and intelligent assistants operate alongside human auditors.

The growing use of AI in auditing also affects the performance of audit teams and the distribution of work between humans and intelligent systems. AI can support auditors by rapidly analyzing extensive datasets, identifying patterns that may escape conventional procedures, and generating decision-relevant information. Such capabilities may improve coordination, reduce cognitive burden, and enhance the ability of audit teams to focus on strategically significant issues. Research has suggested that the integration of AI into audit teams can contribute to improved team performance when technological capabilities are aligned with task characteristics and human expertise [9]. At the same time, effective human-AI collaboration requires auditors to understand the capabilities and limitations of intelligent systems. Professional judgment remains indispensable because AI-generated outputs may depend on training data, algorithm design, assumptions, and contextual factors that require human interpretation. Therefore, the increasing sophistication of technological tools does not eliminate the role of auditors; rather, it changes that role from predominantly executing procedures toward supervising automated processes, interpreting analytical outputs, challenging system-generated conclusions, and exercising professional judgment in technologically complex environments.

Recent developments in generative artificial intelligence further extend the scope of intelligent auditing. Generative AI systems can assist with document analysis, summarization, report preparation, interpretation of textual evidence, communication of audit findings, and interaction with large repositories of accounting and regulatory information. Their integration into audit organizations may require substantial organizational adaptation because the adoption of intelligent technologies depends on dynamic capabilities, including the ability to identify emerging technological opportunities, mobilize organizational resources, and reconfigure work routines. Studies based on dynamic capability perspectives have emphasized that the value of generative AI in auditing depends on how effectively organizations adapt their processes, competencies, and governance arrangements to support intelligent auditing [10]. Accordingly, successful technological transformation involves more than purchasing software or adopting individual tools; it requires continuous organizational learning and the redesign of audit activities around emerging technological capabilities.

Advanced AI applications are also expanding into specialized auditing domains. For example, reinforcement learning and intelligent anomaly analysis have been applied to ESG auditing, where audit decisions may involve complex, multidimensional, and dynamic datasets. Intelligent systems can potentially support adaptive decision-making by learning from changing conditions and identifying unusual patterns in environmental, social, and governance information [11]. This illustrates a broader transition in auditing from static and retrospective procedures toward adaptive, continuous, and data-driven forms of assurance. As organizational reporting increasingly includes nonfinancial information and as stakeholders demand more timely assurance, advanced technologies may enable auditors to evaluate larger and more heterogeneous datasets in near real time. Such developments increase the strategic significance of technological capabilities within audit organizations.

Despite these potential advantages, technology adoption in auditing is influenced by multiple organizational, professional, behavioral, and environmental factors. The introduction of AI and automation requires appropriate technological infrastructure, access to reliable data, integration with client systems, adequate investment, management support, and organizational willingness to redesign established practices. System dynamics research on AI adoption in auditing emphasizes that adoption is influenced by interacting mechanisms rather than isolated

determinants, including perceived benefits, costs, skills, organizational readiness, risk, and institutional pressures [12]. The process is therefore path-dependent and may be reinforced or constrained over time by feedback relationships among investment, experience, trust, competency development, and perceived usefulness. This perspective is particularly important because audit organizations differ substantially in technological maturity, available resources, client characteristics, and readiness for digital transformation.

Auditor competence constitutes another central factor in the adoption and effective use of advanced technologies. The transition toward digital auditing requires knowledge that extends beyond traditional accounting and auditing principles to include data analytics, information systems, cybersecurity, algorithmic logic, automation, and digital risk. The development of such competencies must begin not only within audit firms but also in accounting and auditing education. Research concerning intentions to learn audit software has shown that technology acceptance, expected performance benefits, social influences, self-efficacy, and behavioral factors can affect willingness to develop digital audit capabilities [13]. These findings indicate that technological transformation depends partly on whether current and future auditors perceive digital tools as useful, accessible, and relevant to their professional roles. Continuous professional education therefore becomes essential because the rapid pace of technological development can quickly render existing competencies insufficient.

The expansion of automated and AI-enabled auditing also introduces ethical, legal, and governance challenges. Audit evidence processed through intelligent systems may involve confidential financial information, personal data, proprietary algorithms, and automated decision processes whose logic may not always be transparent. Ethical risks may arise from algorithmic bias, insufficient explainability, data privacy violations, cybersecurity threats, and excessive reliance on automated recommendations. Research on the adoption of AI in auditing has demonstrated that perceived risks and ethical concerns can influence organizational willingness to adopt such technologies [14]. The challenge is particularly significant because auditors retain professional responsibility for conclusions even when substantial components of the audit process are supported by automated systems. Consequently, governance structures must define accountability, validation procedures, access controls, data governance responsibilities, and appropriate levels of human oversight.

Technology-enabled auditing is also increasingly relevant within public-sector and regulatory environments. The implementation of information technology audit systems in tax administration demonstrates how digital auditing can contribute to risk governance, fiscal integrity, control effectiveness, and the detection of irregularities across large administrative datasets [15]. However, these applications also illustrate the need for strong governance because technology-based control systems operate within institutional environments in which errors, cybersecurity incidents, weak data quality, or inappropriate system configurations may have widespread consequences. Therefore, digital auditing should be conceptualized within a broader risk-governance framework that incorporates technological capability, information security, institutional accountability, and continuous evaluation of system performance.

The potential of AI and automation to mitigate audit risk represents another major area of interest. Automated analysis can expand audit coverage, enable continuous examination, identify unusual transactions, and support more systematic risk prioritization. Artificial intelligence may further improve the recognition of complex relationships and anomalies that are difficult to detect through traditional analytical procedures. Accordingly, the combined use of RPA and AI has been proposed as an important mechanism for reducing audit risk and improving the efficiency of audit procedures [16]. Nevertheless, technological tools can create new forms of model risk, cybersecurity risk, data-quality risk, and reliance risk. The reduction of traditional audit risks may therefore be

accompanied by the emergence of technologically mediated risks, making risk governance an essential component of advanced audit systems.

The continuity and future relevance of the auditing profession are closely connected to its ability to adapt to these technological developments. Digitalization and automation are changing both the economics and professional identity of auditing by reducing the importance of some routine activities while increasing demand for analytical, technological, and advisory capabilities. The future of auditing is therefore likely to depend on the capacity of professionals and firms to integrate technology without compromising independence, professional skepticism, ethical responsibility, and audit quality [2]. Rather than replacing auditors entirely, automation is more likely to alter the composition of audit work and redefine the capabilities required for professional practice. Auditors who can combine accounting expertise with technological understanding and critical judgment may occupy an increasingly important role in evaluating complex digital business environments.

Recent expert-based research also indicates that the role of advanced technology and automation in auditing will continue to expand. Delphi evidence suggests that advanced technologies are expected to become embedded across multiple stages of the audit process, including planning, evidence collection, testing, risk assessment, documentation, and reporting [17]. The significance of this development lies in the need for an integrated perspective. Much of the existing literature has examined specific technologies such as RPA, AI, generative AI, or machine learning separately, while professional practice increasingly involves combinations of technologies operating within interconnected systems. A comprehensive model is therefore required to explain how technological infrastructure, organizational readiness, auditor capabilities, regulatory and ethical governance, implementation barriers, technology adoption, process transformation, and audit outcomes interact.

The opportunities and challenges associated with AI-based decision-making further reinforce the need for such an integrated framework. AI can facilitate faster analysis, improve detection capabilities, and support decision-making, but its benefits are conditional on organizational readiness, data quality, technological competence, and appropriate governance. Research examining AI-based decision-making in the audit process has emphasized the coexistence of substantial opportunities and implementation challenges, demonstrating that technological adoption must be assessed as a multidimensional organizational phenomenon rather than solely as a technical innovation [18]. Similarly, the literature suggests that the success of advanced audit technologies depends on managing both enabling factors and constraints simultaneously. Technologies should therefore be evaluated not only in terms of technical sophistication but also according to their capacity to transform audit processes and generate measurable improvements in quality, efficiency, accuracy, and professional decision-making.

Collectively, prior studies demonstrate the substantial potential of advanced technologies and automation to reshape auditing, while also revealing fragmentation in current knowledge. Research has documented the benefits of RPA for repetitive tasks, the effects of automation on audit quality, the contribution of AI to audit risk assessment and team performance, the emerging role of generative AI, the significance of technology acceptance and digital competencies, and the importance of ethical and governance considerations [5, 6, 9, 10]. Systematic reviews further indicate that AI and automation are becoming central themes in contemporary auditing research, yet greater conceptual integration is required to explain how these technologies interact with organizational and professional conditions [1, 8]. Therefore, an integrated model that simultaneously incorporates enabling infrastructure, organizational readiness, auditor digital competencies, regulatory and ethical governance, implementation barriers and risks, technological adoption, audit process transformation, and resulting audit outcomes can provide a more comprehensive understanding of technological transformation in the auditing profession.

Accordingly, the aim of the present study was to develop and validate an integrated model for the application of advanced technologies and automation in the auditing profession by identifying its principal technological, organizational, professional, regulatory, and implementation dimensions and examining their relationships with audit process transformation and audit outcomes.

2. Methods and Materials

The present study was an applied study in terms of purpose and an exploratory study in terms of research approach, conducted with the aim of developing a comprehensive model for the application of advanced technologies and automation in the auditing profession. Given the emerging and multidimensional nature of technological transformation in auditing, an exploratory approach was adopted to identify, refine, and organize the factors affecting the adoption and effective application of advanced technologies and automation in audit activities. The research process was conducted in sequential stages combining expert-based qualitative inquiry with quantitative assessment of the resulting framework in Tehran. In the first stage, the conceptual domain of the study was examined through a review of the relevant theoretical and empirical literature concerning audit technologies, artificial intelligence, robotic process automation, data analytics, blockchain, cloud-based audit systems, continuous auditing, machine learning, and other technology-enabled auditing practices. Subsequently, semi-structured in-depth interviews were conducted with experts to identify the major dimensions, components, indicators, facilitating conditions, barriers, and consequences associated with the application of advanced technologies and automation in the auditing profession. The statistical population of the qualitative phase consisted of individuals possessing substantial theoretical or practical expertise in auditing, accounting information systems, digital transformation, information technology, or technology-based auditing. Participants were selected through purposive and judgmental sampling, with emphasis on information richness and direct professional experience. Eligibility criteria included having relevant academic specialization or professional qualifications, substantial experience in auditing or related technological fields, familiarity with emerging technologies applicable to auditing, and willingness to participate in the study. Sampling and interviewing continued until data saturation was achieved, meaning that additional interviews no longer produced substantially new concepts or categories. In the subsequent quantitative stage, the indicators extracted from the qualitative phase were transformed into a structured questionnaire and administered to a larger group of auditing professionals and experts in order to evaluate the proposed relationships and validate the measurement and structural dimensions of the model. Participation in all stages was voluntary, participants were informed of the purpose of the study, and confidentiality of personal and professional information was maintained throughout the research process.

Data collection was performed in several complementary stages using both qualitative and quantitative instruments. During the qualitative stage, the principal data collection instrument was an in-depth semi-structured interview guide developed on the basis of the objectives of the study and the initial review of the literature. The interview questions were designed to encourage participants to explain their perceptions and professional experiences regarding the current and potential applications of advanced technologies and automation in auditing, technological infrastructure requirements, organizational and professional readiness, auditors' technological competencies, regulatory and ethical considerations, perceived advantages and risks, implementation barriers, and expected consequences of technology-based transformation in audit procedures. The semi-structured format enabled the researcher to maintain consistency across interviews while simultaneously allowing additional probing questions to be asked whenever participants introduced new or particularly relevant issues. Before the principal

interviews, the interview protocol was reviewed by experts to ensure clarity, relevance, comprehensiveness, and consistency with the research objectives. Interviews were conducted individually and, with the informed consent of participants, were recorded using a digital audio recorder to ensure accurate preservation of the participants' statements and facilitate verbatim transcription. Where field-based observations were relevant and explicit consent was obtained, photographic or video recording could also be used to document contextual information. In addition, a field notebook and written records were used throughout the interviews to register nonverbal observations, contextual characteristics, emerging interpretations, analytic ideas, and preliminary conceptual relationships immediately during or following each interview. These complementary records were used to strengthen the completeness and credibility of the qualitative dataset.

Following transcription and qualitative analysis of the interviews, the identified concepts, categories, and indicators were converted into questionnaire items for the quantitative phase. The initial questionnaire was submitted to a panel of auditing, accounting, research methodology, and technology experts to assess its content and face validity. Experts examined whether individual items appropriately represented the intended constructs, whether the wording was sufficiently clear and unambiguous, and whether the collection of items adequately covered the conceptual domain of advanced technologies and automation in auditing. Necessary revisions, including modification, combination, elimination, or clarification of individual items, were subsequently made according to expert feedback. The final questionnaire consisted of two principal sections. The first section collected general and professional characteristics of respondents, such as educational background, professional experience, field of expertise, and experience with technology-enabled auditing. The second section contained statements representing the dimensions and components of the proposed model. Responses to the substantive items were recorded using a five-point Likert scale ranging from 1, representing strongly disagree, to 5, representing strongly agree. The reliability of the questionnaire and its individual constructs was subsequently examined through internal consistency coefficients, particularly Cronbach's alpha and composite reliability, while construct validity was evaluated through convergent and discriminant validity procedures during measurement-model assessment. The integration of interview recordings, verbatim transcripts, field notes, expert assessments, and questionnaire responses provided methodological triangulation and strengthened the credibility and robustness of the data collection process.

Data analysis was conducted in accordance with the exploratory and model-development orientation of the study. Qualitative data obtained from the semi-structured interviews were first transcribed verbatim and repeatedly reviewed to develop familiarity with the content. The transcripts were then subjected to systematic coding. Meaningful statements related to the use of advanced technologies and automation in auditing were identified and assigned initial codes. Conceptually similar codes were subsequently compared, refined, and grouped into subcategories, and related subcategories were integrated into broader conceptual categories and dimensions. Constant comparison was used throughout the analysis to identify similarities, differences, relationships, and conceptual boundaries among the emerging categories. The coding process continued iteratively until a coherent conceptual structure describing the antecedents, requirements, technological mechanisms, organizational conditions, professional competencies, barriers, and consequences of advanced technology adoption in auditing was developed. To enhance trustworthiness, coding decisions and category definitions were repeatedly reviewed, the emerging framework was compared with the original interview data, and expert feedback was used to evaluate the conceptual adequacy and interpretability of the proposed model. Credibility was further supported through prolonged engagement with the data, comparison of evidence across participants, maintenance of field

and analytic notes, and examination of the consistency between extracted concepts and participants' professional experiences.

After development of the initial conceptual framework, quantitative data obtained from the questionnaire were analyzed using descriptive and inferential statistical techniques. Descriptive statistics, including frequency, percentage, mean, standard deviation, skewness, and kurtosis, were calculated to summarize participant characteristics and the distribution of responses to the research variables. The measurement properties of the model were then assessed by examining indicator loadings, Cronbach's alpha, composite reliability, and average variance extracted. Values of Cronbach's alpha and composite reliability of at least 0.70 and an average variance extracted of at least 0.50 were considered evidence of acceptable reliability and convergent validity. Discriminant validity was assessed by examining the distinctiveness of the latent constructs, including the heterotrait-monotrait ratio where appropriate, while multicollinearity among predictor constructs was examined using variance inflation factors. After confirmation of the measurement model, the structural model was evaluated to determine the magnitude and statistical significance of the hypothesized relationships among the identified dimensions. Path coefficients, t statistics, significance levels, coefficients of determination, predictive relevance indices, and overall model-fit criteria were examined to assess the explanatory and predictive adequacy of the proposed framework. Bootstrapping was employed to determine the statistical significance of structural relationships. The combination of systematic qualitative analysis and quantitative model validation enabled the development of an empirically grounded and methodologically robust model explaining how advanced technologies and automation can be effectively integrated into the auditing profession.

3. Findings and Results

The qualitative phase of the study included 18 experts selected purposively on the basis of their academic and professional expertise in auditing, accounting information systems, information technology, digital transformation, and technology-enabled assurance services. Of these participants, 14 were male and 4 were female. Their mean age was 46.28 years, with an age range of 34 to 61 years, and their mean professional experience was 18.61 years. Ten participants had doctoral degrees and eight had master's degrees or equivalent professional qualifications. In terms of professional background, the expert panel included university faculty members specializing in accounting and auditing, certified and senior auditors, audit partners and managers, specialists in accounting information systems, and professionals with experience in digital transformation and advanced audit technologies. Data saturation was reached after the sixteenth interview; however, two additional interviews were conducted to ensure that no substantively new conceptual categories emerged. In the quantitative phase, 312 questionnaires were distributed among auditors, audit managers, accounting professionals, and experts familiar with technology-enabled auditing. After excluding questionnaires with substantial missing data or patterned responses, 286 valid questionnaires were retained for analysis, corresponding to a usable response rate of 91.67%. Among the quantitative participants, 204 respondents (71.33%) were male and 82 (28.67%) were female. The mean age of the respondents was 40.76 years, with a standard deviation of 8.42 years, and their mean professional experience was 14.38 years. Regarding education, 74 respondents (25.87%) held bachelor's degrees, 151 (52.80%) held master's degrees, and 61 (21.33%) held doctoral degrees or equivalent advanced professional qualifications. In terms of professional experience, 51 respondents (17.83%) had fewer than 5 years of experience, 72 (25.17%) had 5 to 10 years, 93 (32.52%) had 11 to 20 years, and 70 (24.48%) had more than 20 years of professional experience. Overall, the characteristics of both qualitative and quantitative participants indicated substantial familiarity with auditing practice and sufficient

professional experience to evaluate the requirements and consequences of applying advanced technologies and automation in the auditing profession.

Table 1. Main Dimensions, Components, and Representative Indicators Extracted from the Qualitative Analysis

Main dimension	Components	Representative indicators	Initial codes	Final indicators
Technological Infrastructure	Digital infrastructure; system integration; data accessibility; cybersecurity	Cloud-based audit platforms, integrated information systems, secure databases, interoperability, real-time access to audit evidence, cybersecurity controls	48	8
Organizational Readiness	Strategic support; financial resources; organizational culture; change management	Management commitment, technology investment, innovation-oriented culture, allocation of implementation resources, resistance management	42	7
Auditor Digital Competencies	Technical knowledge; analytical skills; technology acceptance; continuous learning	Data analytics skills, AI literacy, RPA familiarity, professional skepticism in digital environments, continuous professional development	46	8
Advanced Audit Technologies	Artificial intelligence; machine learning; robotic process automation; blockchain; big-data analytics; continuous auditing	Automated testing, anomaly detection, intelligent risk assessment, blockchain-based verification, process automation, continuous monitoring	59	10
Regulatory and Ethical Governance	Professional standards; data governance; privacy; accountability; algorithmic transparency	Confidentiality, data protection, explainability, professional responsibility, audit standards for automated procedures	39	7
Implementation Barriers and Risks	Cost; skill gaps; technological complexity; resistance; security risk	High implementation costs, shortage of skilled personnel, legacy systems, cyber risk, algorithmic bias, resistance to technological change	44	8
Audit Process Transformation	Planning; risk assessment; evidence collection; testing; reporting	Automated planning, continuous risk assessment, digital evidence gathering, automated substantive procedures, technology-assisted reporting	52	9
Audit Outcomes	Audit quality; efficiency; accuracy; fraud detection; decision usefulness	Reduced audit time, improved coverage, fewer human errors, stronger fraud detection, timely reporting, enhanced audit assurance	47	8
Total	32 components	65 retained indicators	377 initial codes	65

The qualitative analysis produced 377 initial codes derived from the verbatim interview transcripts. Through continuous comparison, elimination of repetitions, conceptual integration, and expert review, these initial codes were condensed into 65 final indicators, which were subsequently organized into 32 components and eight higher-order dimensions. As shown in Table 1, the dimension of advanced audit technologies contained the largest number of final indicators, reflecting the diversity of technological mechanisms that experts considered relevant to contemporary auditing. This dimension encompassed artificial intelligence, machine learning, robotic process automation, blockchain, big-data analytics, and continuous auditing technologies. Audit process transformation was also identified as a highly prominent dimension and consisted of indicators related to changes in audit planning, risk assessment, evidence collection, testing procedures, and reporting. Technological infrastructure emerged as a fundamental enabling dimension because participants repeatedly emphasized that advanced audit technologies could not be effectively implemented in the absence of integrated systems, reliable data, adequate computing capacity, secure digital infrastructure, and interoperability between audit and client information

systems. Organizational readiness and auditor digital competencies represented two complementary organizational and human-resource foundations of successful implementation. The interviews further demonstrated that technological adoption in auditing was not merely a technical issue, because regulatory and ethical governance was repeatedly identified as necessary for addressing confidentiality, accountability, privacy, algorithmic transparency, and professional responsibility. Implementation barriers and risks represented constraints that could weaken technological adoption, while audit outcomes represented the principal consequences expected from effective implementation, including greater efficiency, higher audit quality, improved accuracy, broader audit coverage, stronger fraud detection, and more timely audit reporting. The resulting qualitative framework therefore suggested that the application of advanced technologies and automation in auditing should be understood as a multidimensional process involving technological, organizational, professional, regulatory, and operational factors rather than as the isolated acquisition of particular digital tools.

Table 2. Descriptive Statistics, Reliability, and Convergent Validity of the Study Constructs

Construct	Number of items	Mean	SD	Cronbach's alpha	Composite reliability	AVE	Loading range
Technological Infrastructure	8	4.03	0.61	0.912	0.929	0.621	0.721–0.846
Organizational Readiness	7	3.89	0.67	0.901	0.923	0.632	0.734–0.851
Auditor Digital Competencies	8	3.76	0.69	0.918	0.934	0.641	0.739–0.862
Advanced Audit Technologies	10	3.84	0.65	0.936	0.946	0.637	0.728–0.879
Regulatory and Ethical Governance	7	4.11	0.58	0.907	0.926	0.643	0.746–0.857
Implementation Barriers and Risks	8	3.71	0.72	0.914	0.931	0.629	0.723–0.868
Audit Process Transformation	9	3.92	0.63	0.929	0.941	0.646	0.741–0.881
Audit Outcomes	8	4.08	0.59	0.925	0.939	0.658	0.754–0.884

As reported in Table 2, the mean scores of the study constructs ranged from 3.71 to 4.11, indicating that respondents generally expressed moderate-to-high agreement with the relevance of the identified dimensions to the successful application of advanced technologies and automation in auditing. Regulatory and ethical governance obtained the highest mean score (M = 4.11, SD = 0.58), followed by audit outcomes (M = 4.08, SD = 0.59) and technological infrastructure (M = 4.03, SD = 0.61). These findings indicate that respondents considered appropriate governance arrangements, protection of professional and ethical standards, reliable technological infrastructure, and the expected improvement in audit outcomes to be particularly important. Implementation barriers and risks had the lowest mean score (M = 3.71, SD = 0.72), although the mean remained above the midpoint of the response scale, demonstrating that participants also recognized substantial implementation constraints. All Cronbach's alpha coefficients exceeded 0.90, ranging from 0.901 for organizational readiness to 0.936 for advanced audit technologies, demonstrating strong internal consistency. Composite reliability coefficients ranged from 0.923 to 0.946 and were therefore well above the recommended minimum value of 0.70. The average variance extracted values ranged from 0.621 to 0.658, exceeding the conventional threshold of 0.50 for all constructs and confirming acceptable convergent validity. Furthermore, standardized factor loadings ranged from 0.721 to 0.884 and were therefore above the minimum acceptable level. These results collectively confirmed that the indicators adequately represented their corresponding latent constructs and that the measurement model possessed satisfactory internal consistency, indicator reliability, and convergent validity.

Table 3. Discriminant Validity Based on the Heterotrait-Monotrait Ratio

Construct	TI	OR	ADC	AAT	REG	IBR	APT	AO
Technological Infrastructure (TI)	—							
Organizational Readiness (OR)	0.672	—						
Auditor Digital Competencies (ADC)	0.618	0.701	—					
Advanced Audit Technologies (AAT)	0.744	0.731	0.762	—				
Regulatory and Ethical Governance (REG)	0.596	0.641	0.588	0.653	—			
Implementation Barriers and Risks (IBR)	0.514	0.582	0.627	0.604	0.548	—		
Audit Process Transformation (APT)	0.729	0.748	0.756	0.823	0.681	0.612	—	
Audit Outcomes (AO)	0.684	0.703	0.721	0.778	0.694	0.576	0.841	—

Table 3 presents the heterotrait-monotrait ratios used to assess discriminant validity among the latent constructs. All HTMT coefficients were below the conservative threshold of 0.85, ranging from 0.514 to 0.841. The highest coefficient was observed between audit process transformation and audit outcomes (HTMT = 0.841), which was theoretically reasonable because improvements in audit outcomes were expected to be closely associated with changes in audit processes. Nevertheless, this value remained below the threshold, indicating that these two constructs represented empirically distinguishable concepts. The association between advanced audit technologies and audit process transformation was also comparatively strong (HTMT = 0.823), supporting the conceptual proposition that technologies such as artificial intelligence, robotic process automation, big-data analytics, blockchain, and continuous auditing mechanisms are directly related to the transformation of traditional audit procedures. However, the value did not indicate problematic conceptual overlap. The remaining HTMT coefficients were substantially lower, confirming adequate separation among technological infrastructure, organizational readiness, auditor digital competencies, regulatory and ethical governance, implementation barriers and risks, advanced audit technologies, audit process transformation, and audit outcomes. In addition, examination of the variance inflation factors indicated that all VIF values ranged between 1.42 and 3.18, remaining below the conservative threshold of 5.00. Therefore, multicollinearity was not considered a serious problem in the structural model. Taken together, the results supported the discriminant validity of the measurement model and demonstrated that each dimension captured a theoretically and statistically distinct aspect of advanced technology and automation adoption in auditing.

Table 4. Structural Model Path Coefficients and Hypothesis Testing

Structural relationship	β	t	p	Result
Technological Infrastructure → Advanced Audit Technologies	0.286	5.214	<0.001	Supported
Organizational Readiness → Advanced Audit Technologies	0.241	4.687	<0.001	Supported
Auditor Digital Competencies → Advanced Audit Technologies	0.319	6.028	<0.001	Supported
Regulatory and Ethical Governance → Advanced Audit Technologies	0.174	3.462	0.001	Supported
Implementation Barriers and Risks → Advanced Audit Technologies	-0.168	3.187	0.002	Supported
Advanced Audit Technologies → Audit Process Transformation	0.604	12.736	<0.001	Supported
Organizational Readiness → Audit Process Transformation	0.167	3.411	0.001	Supported
Auditor Digital Competencies → Audit Process Transformation	0.192	3.923	<0.001	Supported
Regulatory and Ethical Governance → Audit Process Transformation	0.138	2.984	0.003	Supported
Implementation Barriers and Risks → Audit Process Transformation	-0.121	2.648	0.008	Supported
Audit Process Transformation → Audit Outcomes	0.571	10.921	<0.001	Supported
Advanced Audit Technologies → Audit Outcomes	0.226	4.537	<0.001	Supported
Regulatory and Ethical Governance → Audit Outcomes	0.149	3.126	0.002	Supported

The structural model results presented in Table 4 demonstrated that all proposed relationships were statistically significant. Auditor digital competencies exerted the strongest positive direct effect on the adoption and application of advanced audit technologies ($\beta = 0.319$, $t = 6.028$, $p < 0.001$), indicating that technological knowledge, analytical capabilities, familiarity with digital tools, and continuous professional learning constitute particularly important prerequisites for successful technological adoption. Technological infrastructure also had a significant positive effect on advanced audit technologies ($\beta = 0.286$, $t = 5.214$, $p < 0.001$), followed by organizational readiness ($\beta = 0.241$, $t = 4.687$, $p < 0.001$) and regulatory and ethical governance ($\beta = 0.174$, $t = 3.462$, $p = 0.001$). In contrast, implementation barriers and risks had a significant negative effect on advanced audit technology adoption ($\beta = -0.168$, $t = 3.187$, $p = 0.002$), suggesting that high costs, inadequate skills, legacy information systems, cybersecurity concerns, resistance to technological change, and uncertainties surrounding automated decision-making can restrict successful adoption. Advanced audit technologies exerted a strong positive effect on audit process transformation ($\beta = 0.604$, $t = 12.736$, $p < 0.001$), representing one of the strongest relationships in the model. This result indicated that greater integration of artificial intelligence, robotic process automation, machine learning, data analytics, blockchain, and continuous audit technologies was associated with substantial transformation in audit planning, risk assessment, testing, evidence collection, and reporting. Organizational readiness, auditor digital competencies, and regulatory and ethical governance also exerted significant direct effects on audit process transformation, whereas implementation barriers had a negative effect. Finally, audit process transformation showed the strongest direct relationship with audit outcomes ($\beta = 0.571$, $t = 10.921$, $p < 0.001$), demonstrating that the benefits of advanced technology are realized primarily when technologies result in actual changes to audit processes. Advanced audit technologies also had a direct positive effect on audit outcomes ($\beta = 0.226$, $t = 4.537$, $p < 0.001$), while regulatory and ethical governance had a smaller but statistically significant positive direct effect ($\beta = 0.149$, $t = 3.126$, $p = 0.002$). These findings supported the proposed conceptual model and suggested that technology adoption, process transformation, and professional outcomes represent sequentially connected stages rather than isolated elements.

Table 5. Explanatory Power, Predictive Relevance, Effect Sizes, and Overall Model Assessment

Endogenous construct / criterion	R^2	Adjusted R^2	Q^2	Main predictor	f^2 of main predictor
Advanced Audit Technologies	0.587	0.580	0.362	Auditor Digital Competencies	0.142
Audit Process Transformation	0.671	0.665	0.429	Advanced Audit Technologies	0.468
Audit Outcomes	0.638	0.634	0.417	Audit Process Transformation	0.381
Overall model index		Obtained value		Recommended criterion	
SRMR		0.061		<0.080	
NFI		0.918		>0.900	
RMS_theta		0.107		<0.120	
Average VIF		2.24		<5.00	

As shown in Table 5, the proposed model demonstrated substantial explanatory and predictive power. Technological infrastructure, organizational readiness, auditor digital competencies, regulatory and ethical governance, and implementation barriers collectively explained 58.7% of the variance in advanced audit technologies ($R^2 = 0.587$), indicating that the identified antecedent factors accounted for a considerable proportion of variation in technological adoption. The model explained 67.1% of the variance in audit process transformation ($R^2 = 0.671$), representing the highest explanatory power among the endogenous constructs and indicating that the integration of advanced technologies together with organizational, professional, regulatory, and risk-related conditions substantially determined the extent to which auditing procedures were transformed. The model also

explained 63.8% of the variance in audit outcomes (R^2 = 0.638), demonstrating that technology-enabled transformation accounted for a substantial proportion of improvements in audit quality, efficiency, accuracy, fraud detection, coverage, and timeliness. All Q^2 values were greater than zero and ranged from 0.362 to 0.429, confirming satisfactory predictive relevance. Examination of effect sizes showed that advanced audit technologies had a large effect on audit process transformation (f^2 = 0.468), while audit process transformation had a large effect on audit outcomes (f^2 = 0.381). Auditor digital competencies had a moderate effect on advanced audit technology adoption (f^2 = 0.142), indicating the importance of human capital and technological capability. The standardized root mean square residual was 0.061, below the recommended maximum of 0.08, while the normed fit index was 0.918, exceeding the desirable threshold of 0.90. RMS_theta was 0.107, remaining below 0.12, and the average VIF of 2.24 indicated the absence of problematic multicollinearity. These indices collectively demonstrated that the proposed model provided an acceptable representation of the observed data and possessed adequate explanatory, predictive, and overall structural quality.

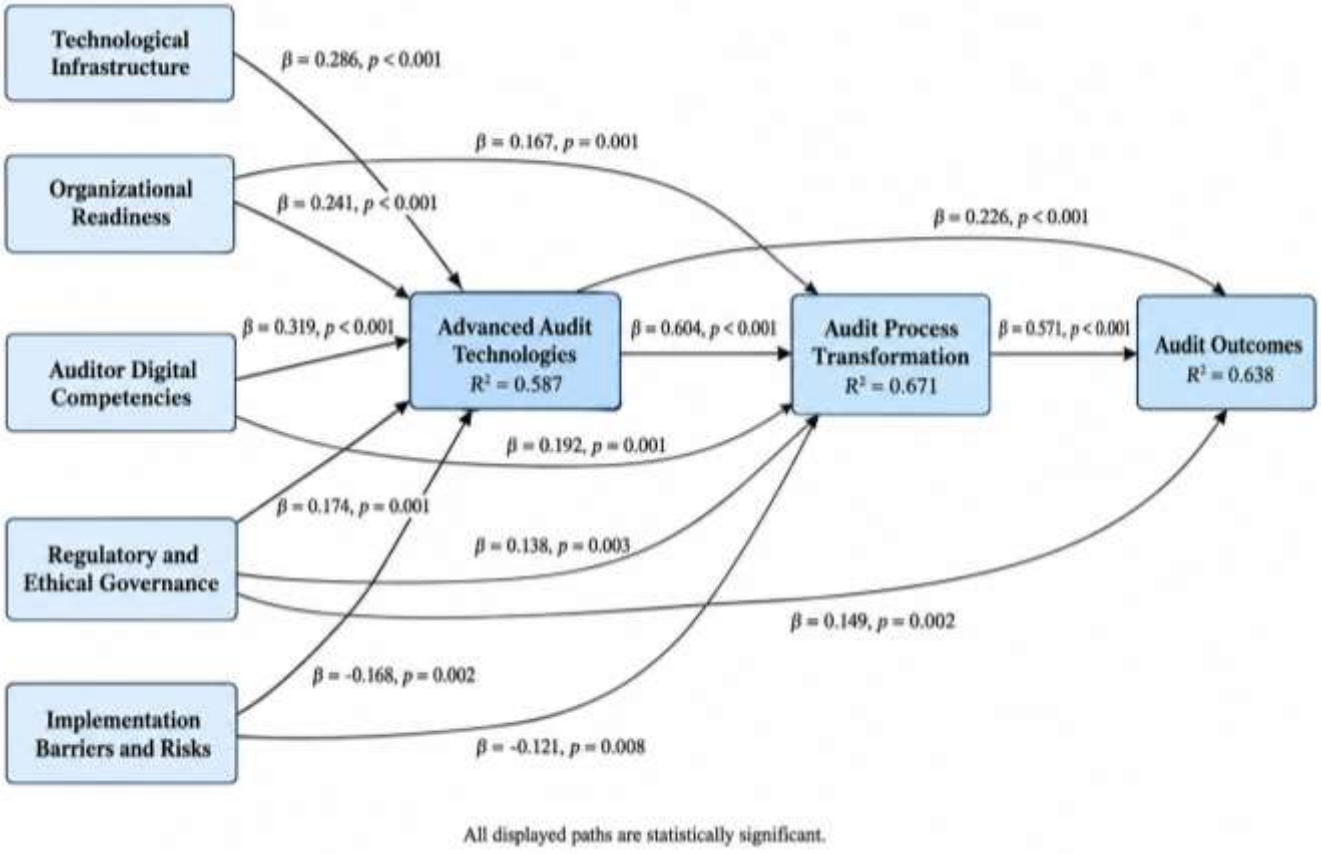


Figure 1. Proposed Model for the Application of Advanced Technologies and Automation in the Auditing Profession

The final model indicated a coherent sequence through which advanced technologies and automation can contribute to improved auditing outcomes. At the first level, technological infrastructure, organizational readiness, auditor digital competencies, and regulatory and ethical governance functioned as enabling conditions, whereas implementation barriers and risks operated as inhibiting conditions. Among these antecedents, auditor digital competencies demonstrated the strongest direct contribution to advanced technology adoption, emphasizing that access to sophisticated technologies alone is insufficient unless auditors possess the knowledge and skills required to use them appropriately. At the second level, the actual application of advanced audit technologies represented

the central mechanism connecting organizational and professional readiness to technological transformation of audit procedures. The strong path from advanced audit technologies to audit process transformation demonstrated that technologies become valuable when incorporated into core audit activities rather than used merely as supplementary administrative tools. At the third level, audit process transformation represented the most important immediate determinant of audit outcomes. This finding indicated that improvements in audit quality, efficiency, accuracy, fraud detection, timeliness, and decision usefulness are primarily achieved through redesigning and automating audit procedures. The simultaneous direct effect of advanced audit technologies on audit outcomes suggested that some benefits may also emerge immediately from technological adoption, although the stronger effect through audit process transformation demonstrated that procedural integration is a central mechanism through which technological advantages are realized.

Additional examination of indirect effects provided further support for the mediating role of audit process transformation. The indirect effect of advanced audit technologies on audit outcomes through audit process transformation was statistically significant ($\beta = 0.345$, $t = 8.476$, $p < 0.001$). Because the direct relationship between advanced audit technologies and audit outcomes also remained significant ($\beta = 0.226$, $p < 0.001$), audit process transformation was identified as a partial mediator of this relationship. This means that advanced technologies improved audit outcomes both directly and indirectly through their ability to transform audit processes. The indirect effects of technological infrastructure, organizational readiness, auditor digital competencies, and regulatory and ethical governance on audit outcomes were also significant through the sequential mechanisms of advanced technology adoption and audit process transformation. Among these antecedent variables, auditor digital competencies produced the strongest overall indirect effect, reinforcing the importance of auditors' technological skills in determining whether investment in automation produces meaningful professional outcomes. Conversely, implementation barriers and risks exerted a negative indirect effect on audit outcomes by weakening technology adoption and limiting process transformation.

Overall, the findings demonstrated that the application of advanced technologies and automation in the auditing profession is a systemic and multilevel phenomenon. Effective implementation depends not only on the availability of artificial intelligence, machine learning, robotic process automation, blockchain, big-data analytics, cloud technologies, and continuous auditing systems, but also on the existence of adequate technological infrastructure, organizational preparedness, skilled auditors, and appropriate regulatory and ethical governance. The results further showed that implementation barriers can meaningfully restrict technological integration and therefore require active management. Most importantly, the findings indicated that audit process transformation constitutes the principal pathway through which advanced technologies generate professional value. Accordingly, the proposed model suggests that audit firms and professional institutions should not evaluate technological development merely in terms of the number of digital tools acquired or implemented; rather, technological maturity should be assessed according to the degree to which these technologies become integrated into audit planning, risk assessment, evidence collection, substantive and control testing, anomaly and fraud detection, continuous monitoring, and audit reporting. The final validated model therefore provides an integrated explanation of the conditions, mechanisms, and outcomes associated with the application of advanced technologies and automation in the auditing profession.

4. Discussion and Conclusion

The present study developed and validated an integrated model for the application of advanced technologies and automation in the auditing profession. The findings showed that the proposed model possessed satisfactory explanatory and predictive power and that technological infrastructure, organizational readiness, auditor digital competencies, regulatory and ethical governance, and implementation barriers and risks significantly influenced the adoption of advanced audit technologies. Among these antecedents, auditor digital competencies had the strongest positive effect on advanced audit technologies, followed by technological infrastructure and organizational readiness. Regulatory and ethical governance also exerted a significant positive effect, whereas implementation barriers and risks had a significant negative effect. In addition, advanced audit technologies had a strong positive effect on audit process transformation, while audit process transformation exerted the strongest direct effect on audit outcomes. The model also showed that advanced audit technologies had a significant direct effect on audit outcomes and that audit process transformation partially mediated this relationship. These results collectively indicate that technological transformation in auditing is not simply the result of adopting individual digital tools; rather, it is a systemic process in which technological resources, organizational preparedness, professional capabilities, governance structures, and implementation constraints interact to determine whether technology is successfully embedded in audit processes and translated into meaningful professional outcomes.

The finding that auditor digital competencies exerted the strongest direct effect on the application of advanced audit technologies highlights the central role of human capital in digital audit transformation. This result suggests that even when advanced software, data platforms, automation tools, and artificial intelligence systems are available, their practical value remains limited if auditors lack the ability to understand, operate, interpret, and critically evaluate them. Digital competence in auditing extends beyond basic technical proficiency and includes data analytics skills, familiarity with AI-assisted tools, understanding of automated workflows, awareness of algorithmic limitations, ability to interpret system-generated outputs, and capacity to exercise professional skepticism in technology-mediated environments. This finding is consistent with studies emphasizing that the successful adoption of audit software and intelligent technologies depends heavily on users' technological knowledge, perceived capability, self-efficacy, and willingness to learn new systems [13]. It is also compatible with research showing that AI can enhance audit team performance when auditors are capable of integrating technological outputs with professional expertise and collaborative decision-making [9]. Therefore, the present findings support the view that the future effectiveness of audit automation depends as much on the capabilities of auditors as on the sophistication of the technologies themselves.

The significant positive effect of technological infrastructure on advanced audit technology adoption further confirms that the application of intelligent and automated auditing requires a reliable digital foundation. The use of artificial intelligence, robotic process automation, continuous auditing, big-data analytics, and cloud-based platforms depends on the availability of integrated information systems, secure data access, processing capacity, interoperability, cybersecurity controls, and reliable digital records. Without such infrastructure, advanced technologies may remain fragmented, underutilized, or limited to isolated tasks. This finding is consistent with the broader literature on AI and automation in auditing, which emphasizes that digital transformation requires suitable technological ecosystems rather than the isolated acquisition of individual tools [1]. Similarly, research on RPA implementation demonstrates that automation is most effective when tasks, systems, and data flows are sufficiently standardized and technologically integrated to support automated execution [5]. The result therefore suggests that

audit organizations seeking to expand automation should first evaluate the maturity, integration, security, and accessibility of their technological infrastructure before attempting large-scale implementation.

Organizational readiness also had a significant positive effect on the adoption of advanced audit technologies and on audit process transformation. This finding indicates that technology implementation is strongly influenced by managerial commitment, availability of financial resources, strategic orientation toward innovation, organizational culture, and the ability to manage change. Advanced audit systems often require substantial investment, redesign of workflows, employee training, and coordination among audit, information technology, and management functions. Organizations that view technology as a strategic capability rather than a peripheral operational tool are therefore more likely to integrate it successfully into audit processes. This result corresponds with research emphasizing organizational adaptation as a major condition for intelligent auditing. In particular, generative AI-enabled auditing requires organizations to develop dynamic capabilities that allow them to identify technological opportunities, mobilize resources, and restructure work processes in response to technological change [10]. Likewise, system dynamics perspectives on AI adoption show that organizational readiness interacts with learning, experience, investment, trust, and perceived benefits over time [12]. The present results therefore reinforce the idea that audit technology adoption should be treated as an organizational transformation initiative rather than as a purely technical implementation project.

The significant positive effect of regulatory and ethical governance on both advanced audit technology adoption and audit outcomes is another important finding. The growing use of AI and automated systems raises concerns regarding data privacy, confidentiality, professional accountability, explainability, algorithmic bias, cybersecurity, and the reliability of machine-generated recommendations. In the absence of clear governance structures, auditors may be reluctant to rely on automated tools, and organizations may face greater legal and professional uncertainty. The current finding indicates that appropriate rules, standards, oversight mechanisms, data governance arrangements, and ethical controls can increase confidence in advanced technologies and support their responsible use. This result is aligned with research showing that perceived ethical issues and technology-related risks significantly influence AI adoption in auditing [14]. It is also compatible with studies of technology-enabled audit systems in public-sector and tax environments, where risk governance, information security, and accountability are necessary for preserving digital fiscal integrity [15]. Thus, regulatory and ethical governance should not be interpreted merely as a constraint on technological innovation; rather, it can function as an enabling condition by establishing the trust and accountability required for wider and more effective adoption.

In contrast, implementation barriers and risks had significant negative effects on advanced audit technology adoption and audit process transformation. This finding demonstrates that technological transformation may be inhibited by high implementation costs, shortages of skilled personnel, legacy systems, resistance to change, cybersecurity concerns, complexity of integration, and uncertainty regarding automated decision-making. Such barriers may be particularly influential in smaller audit firms or organizations with limited technological maturity. The negative relationship identified in this study is consistent with existing research indicating that although automation can improve audit quality and efficiency, implementation difficulties can reduce its practical effectiveness [6, 7]. It also aligns with research emphasizing that the adoption of AI involves both substantial opportunities and meaningful challenges, including organizational, professional, and technological constraints [18]. Therefore, the findings suggest that successful digital transformation requires not only investment in enabling factors but also deliberate strategies for identifying and reducing implementation barriers.

A particularly important result was the strong positive effect of advanced audit technologies on audit process transformation. This finding confirms that the value of technology lies primarily in its ability to change how auditing is performed. The application of artificial intelligence, machine learning, robotic process automation, blockchain, data analytics, and continuous auditing can transform audit planning, risk assessment, evidence collection, substantive testing, control testing, anomaly identification, and reporting. The magnitude of this relationship suggests that technological adoption becomes meaningful when advanced systems are embedded into core audit activities rather than used only for administrative support. This result is strongly consistent with the literature on RPA, which demonstrates that automated tools can execute repetitive and rule-based audit tasks, reduce processing time, and improve consistency [3, 4]. It also supports the framework proposed for the systematic application of RPA to audit tasks, in which successful automation depends on identifying appropriate procedures and integrating them into the audit workflow [5]. Furthermore, expert-based research suggests that advanced technologies are increasingly expected to become embedded across multiple stages of the audit process, including planning, testing, evidence gathering, documentation, and reporting [17].

The strongest direct relationship in the structural model was observed between audit process transformation and audit outcomes. This finding indicates that improvements in audit quality, efficiency, accuracy, fraud detection, timeliness, and decision usefulness are primarily achieved through actual changes in audit procedures. Technology itself does not automatically generate superior outcomes; rather, its benefits are realized when audit firms redesign processes and integrate digital capabilities into professional practice. This result provides an important explanation for why some organizations may invest in advanced technologies without experiencing proportional improvements in audit performance. If technology is layered onto traditional procedures without redesigning workflows, the potential benefits may remain limited. The present finding is consistent with research showing that automation and RPA can enhance audit quality when they improve the consistency, coverage, and efficiency of audit procedures [6, 7]. It is also aligned with research on AI and RPA as tools for mitigating audit risk through broader data analysis, anomaly detection, and improved risk assessment [16]. Thus, the transformation of audit processes appears to be the critical mechanism through which technological capabilities are converted into professional value.

The significant direct effect of advanced audit technologies on audit outcomes further suggests that some benefits can emerge independently of broader process transformation. Advanced analytical systems may, for example, identify anomalous transactions more effectively, increase the volume of data examined, or improve the speed of selected procedures even before comprehensive redesign occurs. This result is consistent with systematic evidence showing that AI and automation can contribute directly to efficiency, analytical capability, fraud detection, and audit quality [1, 8]. It is also compatible with research demonstrating that intelligent decision systems can support adaptive anomaly analysis in specialized areas such as ESG auditing [11]. However, the stronger effect of audit process transformation indicates that the full value of advanced technology emerges only when it is embedded in a broader transformation of audit practice.

The mediating effect of audit process transformation is therefore particularly meaningful. The finding that advanced audit technologies influenced audit outcomes both directly and indirectly through process transformation indicates partial mediation. This suggests that technology can produce immediate benefits, but a substantial portion of its effect depends on whether it changes the underlying structure and execution of audit work. The result is consistent with the view that digitalization does not merely automate existing activities but can fundamentally alter the role, workflow, and professional identity of auditors [2]. As routine tasks become

increasingly automated, auditors may devote greater attention to judgment-intensive activities, strategic risk evaluation, interpretation of complex evidence, and communication of insights. In this way, technology influences audit outcomes through both technical efficiency and professional reconfiguration.

The findings also contribute to the debate concerning the continuity and future role of the auditing profession. Rather than indicating that technology simply replaces auditors, the results suggest that advanced technologies change the nature of audit work and increase the importance of higher-level professional capabilities. The strong role of digital competencies, organizational readiness, and governance shows that human and institutional factors remain central even as automation becomes more sophisticated. This is consistent with the argument that the continuity of the auditing profession depends on its ability to adapt to digitalization while preserving professional skepticism, independence, accountability, and judgment [2]. It also corresponds with evidence that AI can enhance team performance when human expertise and intelligent systems are integrated effectively [9]. Accordingly, the future auditor is likely to function increasingly as an evaluator, interpreter, supervisor, and decision-maker within technology-enabled audit environments.

Overall, the results support an integrated interpretation of advanced technology adoption in auditing. The proposed model demonstrates that successful implementation depends on a chain of interrelated conditions. Technological infrastructure provides the digital foundation; organizational readiness supplies strategic and operational support; auditor digital competencies enable effective use; regulatory and ethical governance creates trust and accountability; and implementation barriers constrain progress. These factors influence the degree to which advanced audit technologies are adopted, which in turn shapes the transformation of audit processes and ultimately affects professional outcomes. This multidimensional structure is consistent with prior research emphasizing that AI and automation in auditing should be examined through interconnected technological, organizational, professional, and governance perspectives rather than through isolated technological applications [1, 17, 18]. The findings therefore extend the existing literature by integrating these elements into a single explanatory framework and by demonstrating the central mediating role of audit process transformation.

The present study was subject to several limitations that should be considered when interpreting the findings. First, the qualitative phase relied on purposive selection of experts, and although sampling continued until conceptual saturation was reached, the perspectives obtained may not fully represent all segments of the auditing profession. Second, the quantitative phase relied primarily on self-reported questionnaire data, which may be influenced by respondents' perceptions, social desirability, or differing levels of familiarity with advanced technologies. Third, the cross-sectional design limited the ability to examine how technology adoption and audit outcomes develop over time. Fourth, the proposed model focused on broad categories of advanced technologies and did not separately estimate the effects of individual technologies such as artificial intelligence, robotic process automation, blockchain, or generative AI. Finally, organizational differences such as firm size, sector, ownership structure, technological maturity, and client complexity were not modeled as separate contextual variables, although they may influence the strength of the identified relationships.

Future studies are recommended to validate the proposed model in different organizational, professional, and national contexts and to compare the results across audit firms of different sizes and levels of technological maturity. Longitudinal studies could examine how technological adoption, auditor competencies, process transformation, and audit outcomes evolve over time and whether the relationships identified in the present model strengthen or weaken as organizations gain implementation experience. Future research could also investigate the effects of specific technologies separately, including generative artificial intelligence, machine learning, blockchain,

process mining, continuous auditing systems, and robotic process automation. Experimental or field-based studies could provide stronger causal evidence regarding the effects of automation on audit quality, professional judgment, fraud detection, and decision-making. Additional models may also incorporate moderators such as firm size, technological maturity, auditor experience, task complexity, regulatory environment, trust in AI, and management support. Comparative studies between public-sector and private-sector auditing could further clarify how institutional context shapes digital transformation.

Audit firms and professional institutions should approach advanced technology adoption as a strategic transformation program rather than as the isolated purchase of software. Priority should be given to developing auditors' digital competencies through continuous training in data analytics, artificial intelligence, automation, cybersecurity, and technology-assisted audit methods. Organizations should simultaneously invest in secure and integrated digital infrastructure and ensure that information systems provide reliable, accessible, and sufficiently standardized data for automated analysis. Management should establish clear implementation roadmaps, allocate appropriate financial and human resources, and actively manage employee resistance to technological change. Professional bodies and audit organizations should also develop governance frameworks defining accountability for automated decisions, data confidentiality, algorithm validation, human oversight, and documentation requirements. Finally, audit firms should redesign audit workflows so that automation reduces repetitive work while auditors focus increasingly on risk assessment, professional skepticism, interpretation, and complex judgment. Performance evaluation should therefore focus not only on the extent of technology adoption but also on whether technology produces measurable improvements in audit quality, efficiency, accuracy, coverage, fraud detection, and reporting timeliness.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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