Examining the Barriers to and Strategies for Artificial Intelligence Adoption in Audit Institutions: A Qualitative Grounded Theory Study

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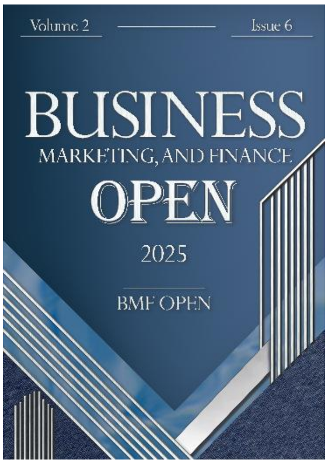

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Abstract: This study aimed to investigate the process of artificial intelligence adoption in public-sector audit institutions using the qualitative grounded theory method. The required data were collected through in-depth semi-structured interviews with senior managers, auditors, and information technology specialists and were analyzed using the three-stage process of open, axial, and selective coding. The findings indicated that the central phenomenon underlying this process was the "transition from traditional auditing to intelligent auditing." This phenomenon is shaped by causal conditions, including increasing pressure for efficiency and transparency, as well as intervening conditions, such as role conflict and the absence of adequate infrastructure. In response to this phenomenon, the principal actors employ a strategy of "stepwise implementation and proof of concept," which ultimately leads to a transition toward an analytical–supervisory role and enhanced organizational legitimacy. The final model developed in this study, which emerged from the grounded theory analysis, can serve as a roadmap for policymakers and managers of audit institutions seeking to achieve the successful adoption of artificial intelligence.

Keywords: Artificial intelligence, auditing, technology–organization–environment model, institutional theory, grounded theory

1. Introduction

Artificial intelligence (AI) has emerged as one of the most consequential drivers of organizational transformation in the contemporary digital economy. Its capacity to process large volumes of heterogeneous data, identify complex patterns, automate repetitive tasks, and support predictive decision-making has altered the operational logic of both private- and public-sector organizations. Digital transformation, however, is not limited to the acquisition of new technological tools; rather, it involves fundamental changes in organizational structures, business processes, professional roles, value-creation mechanisms, and relationships with stakeholders [1]. Within the public sector, AI is increasingly employed to improve service delivery, allocate resources, detect irregularities, enhance regulatory oversight, and support evidence-based policymaking. Nevertheless, public organizations often face distinctive institutional, legal, ethical, and administrative constraints that make the adoption of AI more complex than its implementation in commercially oriented organizations [2]. As governments seek to strengthen digital capacity, improve administrative efficiency, and respond to increasing demands for transparency, accountability, and responsiveness, the maturity of public-sector digital infrastructure has become a critical determinant of successful technological transformation [3].

Auditing represents one of the professional fields most directly affected by advances in AI, data analytics, machine learning, and automated information processing. Traditional auditing has generally relied on periodic examinations, sampling procedures, manual document reviews, retrospective controls, and auditors' professional judgment. Although these practices remain essential, they are increasingly challenged by the scale, speed, variety, and complexity of contemporary organizational data. Modern organizations produce extensive digital records across financial, operational, administrative, and communication systems, making conventional sample-based procedures insufficient for identifying all relevant risks and anomalies. Big data and advanced analytics can expand audit coverage, enable the examination of entire populations of transactions, facilitate the integration of financial and nonfinancial information, and support more timely and precise risk assessments [4]. Similarly, the growing use of enterprise systems and business analytics has transformed the informational environment of accounting and management, creating opportunities for more integrated, continuous, and strategically relevant analysis [5].

AI-enabled auditing encompasses a range of applications, including automated transaction testing, anomaly detection, fraud-risk assessment, document classification, natural language processing, continuous monitoring, predictive analytics, and intelligent decision support. Machine-learning techniques are particularly valuable for detecting unusual behaviors and deviations from expected patterns in large and complex datasets. These systems can identify anomalies that may indicate error, fraud, control deficiencies, or emerging operational risks, although their effectiveness depends heavily on data quality, model selection, contextual interpretation, and appropriate validation [6]. AI can also improve the risk-assessment process by allowing auditors to recognize patterns and relationships that may not be readily visible through conventional analytical procedures, thereby directing audit attention toward high-risk areas and potentially strengthening fraud detection [7]. Continuous auditing technologies further extend these capabilities by shifting audit activity from periodic, retrospective examination toward more frequent or near-real-time evaluation of transactions, controls, and risk indicators [8].

In public-sector auditing, the significance of these developments is particularly pronounced. Public audit institutions are responsible not only for verifying financial accuracy but also for promoting accountability, safeguarding public resources, assessing compliance, and reinforcing citizens' confidence in governmental institutions. The use of AI can potentially improve the scope, speed, consistency, and precision of public audits, while enabling auditors to allocate more time to complex analytical, evaluative, and supervisory responsibilities. AI may facilitate the detection of irregular expenditures, suspicious procurement patterns, duplicated payments, inefficient resource allocation, and potential compliance failures across large governmental datasets. As a result, AI is increasingly portrayed as a means of ushering public-sector auditing into a new era characterized by enhanced accuracy, accountability, and institutional responsiveness [9]. Recent scholarship similarly suggests that AI can transform public audit practices by supporting data-driven oversight, improving risk identification, automating routine procedures, and strengthening the strategic role of auditors in the digital era [10].

Despite these potential benefits, AI adoption in auditing is neither automatic nor technologically determined. Field evidence indicates that audit organizations experience both substantial opportunities and significant implementation difficulties. These difficulties include limited access to high-quality data, incompatible information systems, shortages of technical expertise, uncertainty regarding model reliability, concerns about explainability, resistance from professionals, insufficient managerial support, and ambiguity surrounding responsibility for AI-assisted judgments [11]. The introduction of AI therefore constitutes an organizational change process rather than a simple technical installation. It alters workflows, redistributes tasks, challenges established professional identities, and requires auditors to combine accounting expertise with data literacy, technological knowledge, and critical interpretation of algorithmic outputs. Consequently, the success of AI adoption depends on how effectively institutions manage interactions among technological capability, organizational preparedness, professional adaptation, regulatory requirements, and environmental pressures.

The implications of AI integration are especially complex for accounting and auditing professions in developing economies. Institutions in these contexts may confront fragmented digital infrastructures, budget constraints, limited access to specialized talent, weak data-governance arrangements, outdated information systems, and uncertainty regarding applicable professional standards. At the same time, they face growing pressure to modernize, respond to expanding digital transactions, and align their practices with international expectations. AI adoption may therefore create both developmental opportunities and new forms of professional vulnerability. It may improve audit quality and efficiency, but it may also intensify concerns about job displacement, skills obsolescence, technological dependence, and unequal access to digital capabilities [12]. Evidence from public audit institutions in developing countries further demonstrates that institutional readiness, technological capacity, human resources, governance structures, and leadership commitment are central to determining whether AI initiatives progress beyond experimentation and become embedded in organizational practice [13].

Organizational readiness is thus a foundational element of AI adoption. Readiness includes not only the availability of hardware, software, networks, and financial resources, but also the presence of appropriate strategies, competent personnel, reliable data, effective governance, supportive leadership, and an organizational culture receptive to change. The technology–organization–environment (TOE) framework provides a useful perspective for understanding how technological characteristics, organizational conditions, and environmental factors jointly influence the adoption of innovations. From this perspective, technological readiness may involve compatibility, complexity, security, scalability, and perceived benefits; organizational readiness may include leadership support, resources, skills, culture, and structural flexibility; and environmental conditions may encompass regulation, stakeholder expectations, competitive pressures, professional norms, and external support. Research on big-data adoption indicates that organizations are more likely to implement advanced technologies when technological resources, organizational capabilities, and environmental incentives are mutually aligned [14].

However, the conventional TOE framework may not fully capture the institutional and administrative dynamics shaping technology adoption in public audit organizations. Audit institutions operate within highly regulated environments and are influenced by accounting standards, governmental directives, administrative procedures, professional expectations, and public accountability requirements. Accordingly, recent technology-adoption research has emphasized the need to extend the TOE framework by incorporating institutional and regulatory considerations. The institutional–technology–organization–environment formulation highlights the influence of accounting regulations, administrative pressures, organizational efficiency expectations, and broader contextual forces on the acceptance of audit technologies [15]. A hybrid approach that integrates TOE and institutional theory is particularly appropriate for public administration because it acknowledges that technological decisions are affected not only by internal efficiency calculations but also by legitimacy concerns, regulatory obligations, and pressures for conformity within organizational fields [16].

Institutional theory provides a deeper explanation of why audit institutions may adopt, resist, or symbolically support AI. Organizations do not make decisions solely on the basis of technical efficiency; they also seek social legitimacy, stability, and conformity with accepted rules and expectations. Institutional environments consist of regulative, normative, and cultural-cognitive elements that shape organizational conduct and define what is considered appropriate, credible, and legitimate [17]. In the context of AI adoption, regulative pressures may arise from laws, government policies, auditing standards, and data-protection requirements. Normative pressures may originate from professional associations, international organizations, auditing norms, and expectations regarding professional competence. Cultural-cognitive pressures may involve deeply embedded assumptions about evidence, expertise, professional judgment, and the reliability of human versus algorithmic decision-making.

Institutional isomorphism also helps explain why organizations may become increasingly similar in their adoption of digital technologies. Coercive pressures can result from governmental mandates, regulatory requirements, or funding conditions; normative pressures may emerge from professional education and standards; and mimetic pressures may lead institutions to imitate organizations perceived as innovative or successful under conditions of uncertainty [18]. Public audit institutions may therefore pursue AI not only because of demonstrated operational advantages, but also because digital transformation has become associated with modernization, professional credibility, and international legitimacy. Nevertheless, formal commitment does not necessarily produce substantive implementation. Institutions may publicly endorse AI while failing to provide sufficient budgets, training, governance mechanisms, or organizational support. This gap between symbolic adoption and operational integration is particularly relevant in environments where technological modernization is institutionally valued but organizational capacity remains limited.

External institutional support can reduce uncertainty and facilitate technological innovation by providing standards, resources, incentives, infrastructure, training, and policy coordination. In the wider digital-transformation literature, institutional support is considered an important factor in enabling innovation and entrepreneurship, particularly when organizations face resource limitations or uncertain technological environments [19]. For public audit institutions, such support may be provided by governments, central audit authorities, professional bodies, universities, international development organizations, and technology partners. Clear regulatory frameworks and professional standards can also help determine acceptable uses of AI, establish accountability for algorithm-assisted decisions, and define requirements for transparency, auditability, and human oversight.

Ethical considerations are inseparable from the adoption of AI in auditing. AI systems may reproduce bias, generate opaque recommendations, compromise privacy, expose sensitive data, or create uncertainty concerning responsibility for errors. Because audit findings can have legal, financial, professional, and reputational consequences, the use of algorithms must be governed by principles of fairness, transparency, accountability, security, explainability, and human supervision. International discussions of AI ethics emphasize proportionality, nondiscrimination, privacy protection, human responsibility, transparency, sustainability, and the need to prevent harm [20]. In data-intensive applications, AI-based profiling also raises concerns regarding consent, informational autonomy, discriminatory categorization, and the ethical use of personal or organizational knowledge [21]. These issues are particularly significant in public auditing, where institutions must balance the benefits of comprehensive data analysis with the protection of legal rights, confidentiality, due process, and public trust.

The "black-box" nature of some AI models represents another important barrier. Auditors are professionally required to gather sufficient and appropriate evidence, exercise judgment, document procedures, and justify conclusions. When an AI system produces a risk score or anomaly classification without an understandable explanation, auditors may be reluctant to rely on its output. This reluctance is not simply resistance to technology; it reflects legitimate concerns regarding evidentiary reliability, professional responsibility, model validation, and defensibility. AI adoption therefore requires explainable systems, robust control mechanisms, clear documentation, and defined boundaries between automated analysis and human judgment. Rather than replacing auditors, effective AI implementation is more likely to augment their capabilities by automating routine procedures while preserving human responsibility for interpretation, contextual evaluation, skepticism, and final decision-making.

Workforce implications are similarly central to the adoption process. AI may reduce the demand for repetitive manual tasks, but it simultaneously increases the need for data analysis, systems thinking, professional skepticism, technological evaluation, and interdisciplinary collaboration. Public-sector organizations may use cognitive technologies to redesign work, redistribute responsibilities, and enable employees to concentrate on complex and higher-value functions [22]. In auditing, this transformation may shift the auditor's role from document checker and transaction verifier toward analytical reviewer, systems evaluator, risk advisor, and supervisory decision-maker. Such a transition can improve job quality and organizational effectiveness, but only when institutions invest in training, role redesign, communication, participation, and change management. Without such measures, employees may interpret AI as a threat to employment, status, autonomy, and accumulated professional expertise.

Leadership commitment is therefore essential. Senior managers determine whether AI is treated as a strategic capability or an isolated technical experiment. Effective leadership involves allocating resources, establishing governance structures, articulating a clear vision, supporting pilot projects, encouraging cross-functional collaboration, and managing employee concerns. In resource-constrained institutions, gradual implementation and proof-of-concept projects may offer a practical strategy for reducing uncertainty and demonstrating value. Small-scale pilots allow institutions to assess data readiness, identify technical and organizational barriers, evaluate ethical and legal risks, and build internal confidence before broader deployment. Successful early projects may also produce visible evidence that strengthens managerial support and encourages wider professional acceptance.

Nevertheless, AI adoption should not be conceptualized as a linear process. It is an iterative transition shaped by feedback, negotiation, learning, resistance, institutional constraints, and evolving technological capacities. Organizations may move between experimentation, partial adoption, temporary withdrawal, redesign, and institutionalization. The complexity of this process suggests that quantitative models based solely on predetermined variables may not sufficiently capture how actors interpret AI, negotiate professional roles, respond to uncertainty, and develop locally appropriate strategies. A qualitative approach is therefore necessary to explore how technological, organizational, environmental, and institutional conditions interact within the lived experiences of managers, auditors, and information technology specialists.

Grounded theory is particularly suitable for examining such an underexplored and process-oriented phenomenon. It enables researchers to generate theoretical explanations directly from systematically collected and analyzed data rather than imposing a fully predetermined model on participants' experiences. Through iterative data collection, constant comparison, theoretical sampling, and the progression from open to axial and selective coding, grounded theory can reveal the conditions, actions, interactions, and consequences that constitute organizational processes [23]. This approach is valuable for investigating AI adoption because it allows the central phenomenon and its related categories to emerge from the accounts of actors directly involved in institutional decision-making, audit operations, and technology implementation.

Although the literature increasingly recognizes the transformative potential of AI in auditing, several gaps remain. Much of the existing research emphasizes technological capabilities, expected benefits, or general adoption factors, while fewer studies investigate the dynamic process through which public audit institutions reconcile traditional professional practices with intelligent auditing. Moreover, the interaction among leadership commitment, cultural resistance, data disorder, infrastructure limitations, legal uncertainty, professional role conflict, environmental pressure, and legitimacy-seeking behavior remains insufficiently explained. This gap is particularly important in public audit institutions, where accountability obligations, institutional rules, public scrutiny, and resource constraints create a distinct adoption context. Developing a grounded, process-based model can therefore clarify not only which barriers and facilitators matter, but also how organizational actors respond to them and how their strategies produce specific professional and institutional consequences.

Accordingly, the aim of this study was to develop a grounded theoretical model explaining the barriers, conditions, strategies, and consequences associated with the process of artificial intelligence adoption in public audit institutions.

2. Methodology

The methodological framework governing this study is grounded theory. This qualitative research strategy, initially developed by Glaser and Strauss, is a systematic and iterative method for generating a rich theory or conceptual model that is grounded in the data themselves. Unlike quantitative studies, which are primarily concerned with testing predetermined hypotheses, the ultimate objective of grounded theory is to "discover" and "develop" a theory that emerges directly from real-world conditions and participants' experiences. The resulting theory or final model should not only provide an in-depth understanding of the phenomenon under investigation but should also be applicable and relevant within the context in which it was developed.

The primary and central instrument used for data collection in this study was the semi-structured interview. By employing a general, predesigned interview guide, this type of interview creates a dynamic balance between structure and flexibility. This approach enables the researcher to ensure that all key areas of the study are addressed while simultaneously providing sufficient scope to explore unexpected insights, detailed explanations, and complex issues raised by the participants. The target population for the interviews consisted of three key groups positioned at the forefront of engagement with the phenomenon under investigation: senior managers, who were responsible for strategic decision-making; senior auditors, who possessed extensive technical knowledge of audit processes; and information technology managers, who served as key facilitators of technology implementation. The simultaneous collection of data from these three groups made it possible to develop a multidimensional and comprehensive perspective on the research problem.

In accordance with the internal logic of grounded theory, sampling in this study was conducted using purposive sampling and, more specifically, theoretical sampling. Within this paradigm, individuals or institutions are selected not randomly or according to a predetermined sample size, but on the basis of theoretical criteria and their capacity to provide rich and relevant information regarding the phenomenon under investigation. Gradually, and concurrently with the processes of data collection and analysis, the researcher determines which group should provide the next sample in order to further develop, compare, or validate the emerging concepts.

Sample size determination in this qualitative method was also governed by the criterion of theoretical saturation. Theoretical saturation refers to the point at which additional interviews no longer provide new data, novel conceptual properties, or further insights concerning the developing categories, and the researcher has achieved conceptual coherence and stability within the model. Accordingly, data collection continued until this critical criterion was met and the theoretical model achieved the required level of maturity and completeness. The open-ended interview questions were selected as presented in Table 1. Table 2 also presents the demographic characteristics of the interview participants. Following the completion and analysis of 15 interviews, theoretical saturation was achieved, and the researchers arrived at a final theoretical model.

Table 1. Interview Questions

Question Category	Question Number	Question Text	Purpose of the Question
Opening question—experience-oriented	1	"Please describe your direct experience of encountering artificial intelligence technologies in your workplace. Are you aware of any concrete examples of the application of these technologies in auditing?"	To collect rich data and real-life narratives for developing initial codes and understanding the research setting.
Process-oriented question—exploration of processes	2	"In your opinion, how does your institution prepare for the adoption of new technologies such as artificial intelligence? Where does this process begin, and what stages does it involve?"	To identify patterns, event sequences, and the dynamic stages of "preparedness" as a central process.
Challenge-oriented question—identification of barriers	3	"In your opinion, what are the greatest challenges to the use of artificial intelligence in auditing? How do these challenges affect daily work?"	To identify the principal categories associated with "barriers" and understand their consequences within the organizational context.
Strategy-oriented question—exploration of solutions	4	"What actions or changes are necessary in your institution for the successful implementation of artificial intelligence? Who should play key roles in this process?"	To develop the category of "strategies and facilitating conditions" and identify the key actors involved in the process.
Context-oriented question—understanding the organizational setting	5	"To what extent is the organizational culture of your institution receptive to innovation and new technologies? Please provide a concrete example."	To understand the "contextual conditions," such as culture, that influence and moderate the central phenomenon.

Table 2. Demographic Characteristics of the Interview Participants

Demographic Variable	Category	Frequency	Percentage
Gender	Male	9	60%
	Female	6	40%
Educational Level	Bachelor's degree	5	33.3%
	Master's degree	8	53.3%
	Doctoral degree	2	13.3%
Length of Service	Less than 5 years	2	13.3%
	5–10 years	4	26.7%
	11–15 years	6	40%
	More than 15 years	3	20%
Organizational Role	Senior manager	3	20%
	Senior auditor	5	33.3%
	Auditor	4	26.7%
	Information technology specialist	3	20%
Level of Familiarity with Artificial Intelligence	Beginner	4	26.7%
	Intermediate	7	46.7%
	Advanced	4	26.7%

The descriptive analysis of the sample characteristics, namely the interview participants, is presented as follows. Sampling was conducted in a manner that covered all levels involved in the artificial intelligence adoption process, ranging from senior managers to operational auditors and technology specialists. Approximately 60% of the participants had more than 10 years of experience in auditing, indicating that they possessed substantial operational experience. More than 65% of the participants held postgraduate qualifications, suggesting that the sample had an appropriate academic background. Although the 60-to-40 gender ratio does not represent complete balance, it reflects the meaningful participation of both genders in the study. An appropriate level of diversity in participants' familiarity with artificial intelligence, ranging from beginner to advanced, contributed to a better understanding of the full spectrum of perspectives. This demographic composition made it possible to obtain diverse and comprehensive viewpoints from all stakeholders involved in the process of artificial intelligence adoption in audit institutions.

3. Findings and Results

In grounded theory, data analysis is conducted through coding. In this method, the interview data, consisting of the interviewees' responses, are carefully analyzed and coded. This process is generally undertaken in three stages: (1) open coding, which involves extracting initial concepts from the data; (2) axial coding, which entails identifying relationships among concepts and forming the principal categories; and (3) selective coding, which involves integrating the categories around a core category and ultimately presenting the final model. When the core category that explains all stages and challenges is expressed as the "process of transitioning from traditional auditing to intelligent auditing," it suggests that audit institutions perceive themselves as being situated at the intersection of two competing worlds: the old world, characterized by rigid regulations, manual methods, and distrust of technology, and the new world, characterized by data-driven practices, speed, and algorithmic transparency. Success therefore depends on "reconciling" these two perspectives.

Table 3 presents the three-stage grounded theory coding process used in the present study to identify a model of the artificial intelligence adoption process in auditing.

Table 3. Grounded Theory Coding of the Artificial Intelligence Adoption Process in Auditing

Selective Coding: Core Category and Dimensions	Axial Coding: Categories and Subcategories	Open Coding: Raw Concepts
Central phenomenon: The process of transitioning from traditional auditing to intelligent auditing—the challenge of reconciling the old and new worlds	Category: Paradoxical leadership commitment Properties: - Verbal support versus failure to allocate resources - Lack of understanding of the return on investment in artificial intelligence - Fear of failure and loss of position	- "Management only talks about it but does not provide a budget." - "Purchasing hardware requires overcoming endless bureaucratic obstacles." - "Our budget is sufficient only for salaries and routine expenses."
	Category: Cultural resistance to algorithmic transparency Properties: - Fear of unemployment and marginalization - Loss of experience-based professional authority - Distrust of "black-box" outputs	- "Older auditors are afraid of losing their jobs." - "They say the robot makes mistakes, although they themselves also make errors." - "The dominant culture is that 'our work is based on paper documentation.'"
Action–interaction strategies: Stepwise implementation and proof of concept	Category: Data disorder as a fundamental barrier Properties: - Absence of integrated standards - Fragmented and siloed information systems - Poor data quality and lack of data reliability	- "Our data are scattered and stored in different formats." - "The old financial system does not produce any standardized output." - "Even the digital data are not reliable."
	Category: Strategy of scaling down success Properties: - Beginning with low-risk pilot projects - Using small successes to attract support - Establishing a "pioneer team" to inspire others	- "First, we jointly make a small project successful." - "We present tangible results to management." - "We identify and train curious auditors."
Causal conditions: Increasing pressure for efficiency and transparency	Category: Governance vacuum and legal uncertainty Properties: - Absence of an accountability framework - Lack of standards for auditing algorithms - Uncertainty regarding the evidentiary value of artificial intelligence-generated documents	- "We do not have any regulations governing the use of artificial intelligence." - "If the system makes an error, who is responsible?" - "The central audit organization has not yet issued any procedures."
	Category: Changing environmental requirements Properties: - New stakeholder expectations regarding accountability - Rapid expansion of	- "The media and the public expect greater transparency." - "The volume of data can no longer be examined using traditional

	digital data - International incentives for digital transformation	methods." - "International institutions have introduced incentives."
Consequences: Emergence of preventive auditing and enhanced institutional legitimacy	Category: Transition toward an analytical–supervisory role Properties: - Releasing time for higher-value activities - Attracting and retaining talented personnel - Increasing public trust and institutional legitimacy	- "Repetitive work has decreased, and we can focus on analysis." - "Younger auditors have become more enthusiastic." - "The quality of our reports and our professional credibility have improved."

The analysis of the codes extracted through the grounded theory method resulted in the development of the research model. The model generated from the research data is presented in Figure 1.

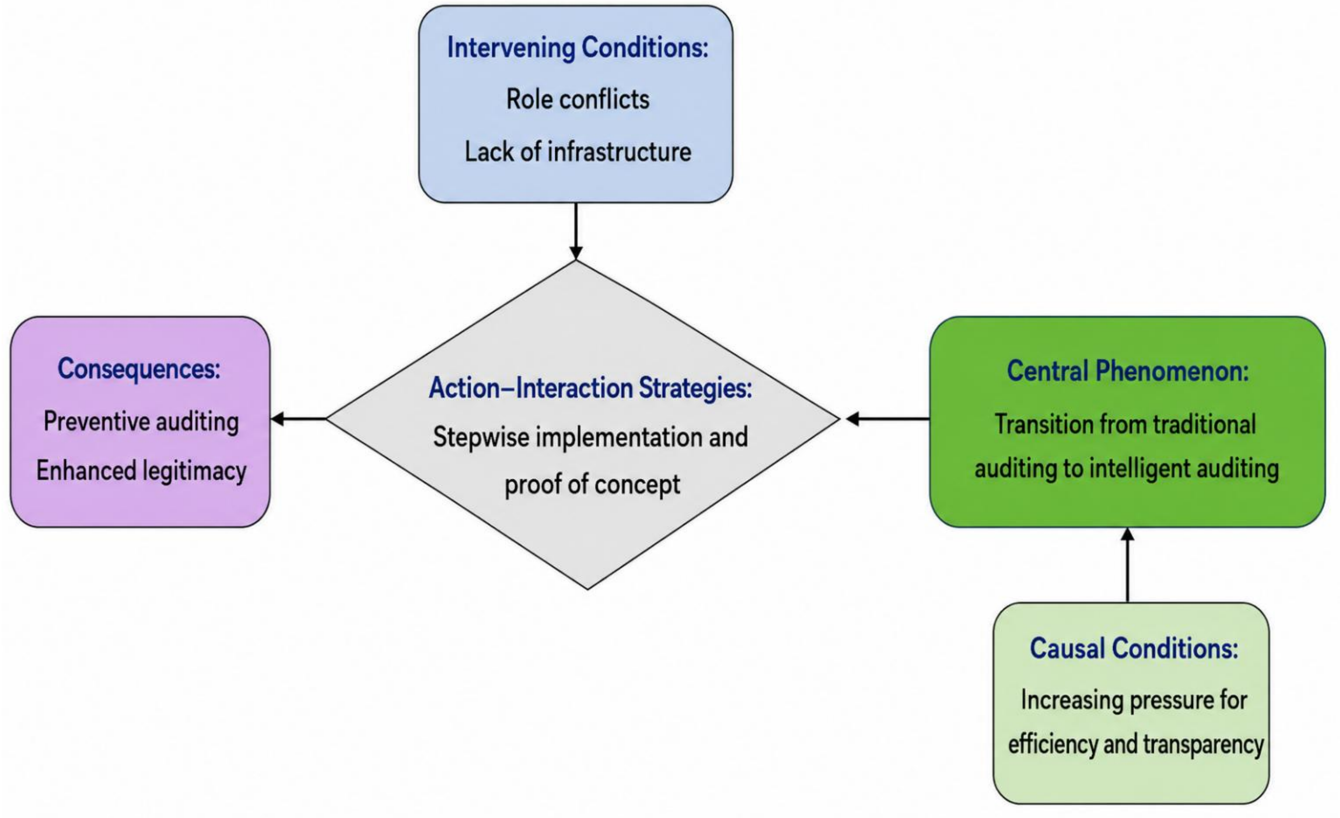

Figure 1. Research Model

In this model:

- **Causal conditions:** Environmental pressures arising from new stakeholder expectations, the rapid expansion of digital data, and international incentives constitute the principal drivers initiating the transformation process.
- **Central phenomenon:** The tension between the "traditional world," characterized by rigid regulations and manual procedures, and the "new world," characterized by data-driven practices, speed, and algorithmic transparency, was identified as the main issue.
- **Intervening conditions:** Barriers such as "role conflict," including fear of unemployment and marginalization, and "lack of infrastructure," including data disorder and a governance vacuum, influence the selection of strategies.
- **Action–interaction strategies:** To overcome these challenges, the principal actors employ a strategy of "stepwise implementation and proof of concept."

- **Consequences:** The successful implementation of these strategies ultimately leads to a "transition toward an analytical–supervisory role" and "enhanced institutional legitimacy."

This model clearly demonstrates how different conditions influence the central phenomenon and how the selected strategies ultimately lead to specific consequences. It can serve as a practical framework for leaders of audit institutions and policymakers, enabling them to determine their current position within this "transition" and understand how the "reconciliation" of these two worlds can be managed.

4. Discussion and Conclusion

The present study sought to explain the process through which public audit institutions adopt artificial intelligence and to identify the barriers, contextual conditions, strategies, and consequences associated with this transformation. The grounded theory analysis showed that the central phenomenon was the transition from traditional auditing to intelligent auditing, a process characterized by tension between established audit practices and emerging data-driven approaches. The findings further indicated that increasing pressures for efficiency and transparency functioned as the principal causal conditions, while role conflict, cultural resistance, fragmented data, weak infrastructure, and governance uncertainty acted as intervening conditions. In response to these challenges, the main actors adopted a strategy of stepwise implementation and proof of concept, relying on small pilot projects, visible early successes, and the engagement of technology-oriented auditors. The anticipated consequences of this process included the emergence of preventive auditing, a transition toward analytical and supervisory roles, improved audit quality, and enhanced institutional legitimacy.

The identification of the transition from traditional auditing to intelligent auditing as the core category reflects the broader transformation occurring within the auditing profession. Traditional audit practices are generally retrospective, periodic, sample-based, and dependent on manual inspection, whereas intelligent auditing relies on automated analysis, continuous monitoring, algorithmic detection, and the examination of large data populations. Previous research has emphasized that the expansion of big data and advanced analytics is changing the structure of audit engagements by enabling broader coverage, more timely analysis, and the detection of patterns that may be overlooked through conventional procedures [4]. Similarly, the growing use of enterprise systems and business analytics has altered the informational foundations of accounting and control, requiring professionals to move beyond routine reporting toward integrated and predictive analysis [5]. The findings of the present study therefore support the view that AI adoption is not merely the introduction of a new tool but a fundamental reconfiguration of professional processes, responsibilities, and decision-making structures.

The tension between the "old world" and the "new world" identified in this study also corresponds with the broader concept of digital transformation. Digital transformation involves major organizational changes in structures, processes, capabilities, and value-creation mechanisms, rather than the isolated digitization of existing activities [1]. In the context of audit institutions, this transformation requires the reconciliation of formal procedures, traditional evidentiary standards, professional skepticism, and experience-based judgment with algorithmic analysis, automated controls, and data-driven decision support. The participants' accounts indicated that these two systems of practice often coexist uneasily. Auditors may recognize the potential value of AI while remaining uncertain about the reliability, interpretability, and professional acceptability of its outputs. This finding is consistent with field evidence showing that the adoption of AI in auditing generates opportunities for efficiency and analytical enhancement but simultaneously raises concerns about trust, explainability, implementation feasibility, and the changing role of professional judgment [11].

The first major causal condition identified in the study was increasing pressure for efficiency and transparency. Participants described growing expectations from citizens, oversight bodies, the media, and other stakeholders for faster, more accurate, and more transparent auditing. They also emphasized that the volume of digital data had expanded beyond the practical capacity of traditional audit techniques. These findings align with previous studies suggesting that public-sector AI adoption is strongly driven by pressures to improve administrative efficiency, accountability, responsiveness, and service quality [2]. Public audit institutions, in particular, are under pressure to demonstrate that public resources are used lawfully and efficiently. AI can support these responsibilities by accelerating data processing, identifying anomalies, and enabling auditors to examine a greater proportion of transactions. The findings also agree with the argument that AI can contribute to a new era of public-sector auditing by strengthening accuracy, oversight, and institutional accountability [9].

The rapid growth of digital data emerged as another important driver of change. Participants reported that conventional audit procedures were no longer sufficient for analyzing the volume and complexity of available information. This result supports the literature on continuous auditing and AI-assisted analysis, which indicates that technological tools can expand the frequency and scope of audit procedures and enable near-real-time monitoring of transactions and controls [8]. Machine-learning techniques are particularly relevant because they can identify unusual transactions, behaviors, and relationships in high-dimensional datasets [6]. The use of AI in risk assessment and fraud detection can therefore shift auditing from retrospective verification toward proactive and preventive oversight [7]. This interpretation is consistent with the consequence identified in the present study, namely the emergence of preventive auditing.

Despite these pressures, the findings showed that organizational readiness was uneven. One of the most prominent barriers was what the participants described as **paradoxical leadership commitment**. Managers often expressed verbal support for AI but failed to allocate sufficient financial, technical, or human resources. This gap suggests that formal endorsement may remain symbolic unless it is supported by tangible organizational action. The result is consistent with the technology–organization–environment perspective, which emphasizes that innovation adoption depends on the alignment of technological capability, organizational readiness, and environmental pressure [14]. Leadership support is important, but its effectiveness depends on resource allocation, strategic planning, governance, and implementation capacity. The findings also align with evidence from public audit institutions in developing countries, where readiness for AI adoption is frequently constrained by limited budgets, weak infrastructure, insufficient skills, and fragmented institutional support [13].

The contradictory nature of leadership support may also be interpreted through institutional theory. Organizations often adopt the language and symbols of modernization to maintain legitimacy, even when internal structures are not fully prepared for substantive change. Institutional theory proposes that organizational behavior is influenced by regulative, normative, and cultural-cognitive pressures, and that institutions seek legitimacy by conforming to socially accepted expectations [17]. In the present study, managerial endorsement of AI appeared partly motivated by external expectations for modernization and digital transformation. However, the absence of budgets and implementation mechanisms revealed a divergence between institutional discourse and operational capacity. This pattern is compatible with the concept of institutional isomorphism, according to which organizations may imitate widely accepted practices or respond to coercive and normative pressures even in the absence of clear internal readiness [18].

Cultural resistance to algorithmic transparency was another central finding. Participants reported that some experienced auditors feared job loss, professional marginalization, and the erosion of authority derived from years of accumulated expertise. They also expressed distrust of "black-box" outputs and preferred paper-based evidence and familiar procedures. These concerns reflect the professional implications of AI adoption in accounting and auditing. Previous research has shown that AI integration can reshape occupational identities, alter required competencies, and generate anxiety about automation and skills obsolescence, particularly in developing economies where access to training may be unequal [12]. The present findings indicate that resistance should not be interpreted merely as conservatism; rather, it may stem from legitimate uncertainty about professional responsibility, technological reliability, and the future distribution of expertise.

This concern is especially important in auditing because professional judgments must be justified, documented, and supported by reliable evidence. When auditors cannot understand how an algorithm has produced a particular output, they may be unwilling to rely on it. The ethical and professional acceptability of AI therefore depends on transparency, explainability, accountability, and human oversight. International discussions of AI ethics emphasize the necessity of preventing discrimination, protecting privacy, ensuring transparency, and maintaining human responsibility for high-impact decisions [20]. Similarly, the use of AI-based profiling and knowledge systems raises concerns regarding fairness, data protection, informed consent, and the misuse of sensitive information [21]. The participants' distrust of black-box systems therefore reflects a broader ethical challenge rather than a simple technological preference.

The findings also revealed that data disorder constituted a fundamental barrier to AI adoption. Participants described scattered data, incompatible formats, outdated financial systems, low data quality, and unreliable digital records. These issues are critical because AI systems depend on consistent, accurate, accessible, and well-governed data. Even advanced algorithms cannot generate reliable insights from incomplete or poorly structured datasets. This result supports research indicating that technological adoption requires appropriate digital infrastructure, integrated information systems, standardized data, and organizational capacity [3]. Public institutions with low digital maturity may struggle to move from experimentation to routine AI use because foundational systems are not sufficiently developed.

The problem of fragmented infrastructure also explains why technological potential does not automatically translate into organizational value. Audit institutions may purchase software or establish pilot programs without first resolving problems of data ownership, access, interoperability, storage, and validation. The TOE framework suggests that compatibility with existing systems is a major determinant of technology adoption [14]. In addition, the extended institutional–technology–organization–environment perspective highlights the importance of administrative regulations, accounting rules, and contextual constraints in shaping the acceptance of audit technologies [15]. The current findings reinforce the need to consider infrastructural, organizational, and institutional readiness simultaneously.

Governance vacuum and legal uncertainty were also identified as important intervening conditions. Participants were uncertain about responsibility for system errors, the evidentiary value of AI-generated outputs, and the absence of official auditing standards for algorithms. These findings demonstrate that technological adoption in public audit institutions cannot proceed solely through internal managerial decisions. AI-assisted auditing requires clear frameworks governing accountability, model validation, data access, documentation, confidentiality, and professional liability. The absence of such frameworks creates hesitation because auditors remain personally and institutionally responsible for conclusions derived from systems they may not fully understand. The result supports the argument that public-sector digital transformation requires institutional coordination and regulatory clarity, not merely technological investment [16].

The regulatory uncertainty observed in the study is also related to the broader role of institutional support. Innovation is more likely to succeed when organizations receive guidance, training, incentives, standards, and resources from the institutional environment [19]. In public auditing, such support may come from central audit authorities, professional associations, governments, universities, and international organizations. Without coordinated support, individual institutions may adopt inconsistent practices, duplicate efforts, or avoid innovation because of legal and professional risks. Therefore, the findings suggest that national and professional governance arrangements should evolve alongside technological capabilities.

The principal strategy identified by participants was **stepwise implementation and proof of concept**. Rather than attempting large-scale implementation, institutions began with small, low-risk pilot projects. These projects were intended to demonstrate tangible value, reduce uncertainty, identify implementation problems, and attract managerial support. This strategy appears particularly appropriate in resource-constrained and risk-sensitive organizations. Pilot projects allow organizations to evaluate the compatibility of AI with current systems, assess data quality, test user responses, and establish realistic performance criteria. They can also generate evidence of efficiency or improved detection that strengthens the case for further investment.

The strategy of using small successes to build support is consistent with the iterative nature of digital transformation. Organizations rarely achieve full technological transformation through a single intervention; instead, they learn through experimentation, feedback, adaptation, and progressive institutionalization [1]. The findings also support the view that AI-augmented public-sector work should be redesigned gradually so that technological capabilities complement rather than abruptly displace human expertise [22]. By beginning with routine or low-risk tasks, audit institutions can demonstrate how AI reduces repetitive workload while retaining human responsibility for interpretation and final judgment.

The creation of a pioneer team was another important component of the strategy. Participants recommended identifying curious, motivated, and technologically receptive auditors and involving them in pilot projects and training. These individuals may act as internal change agents by translating technical knowledge into professional language, demonstrating practical benefits, and reducing resistance among colleagues. This finding is compatible with research showing that AI adoption is more successful when interdisciplinary collaboration connects auditors, managers, and information technology specialists [11]. Such collaboration is essential because AI implementation requires both domain expertise and technological competence.

The consequences identified in the study included a transition toward analytical and supervisory roles, reduced repetitive work, greater attractiveness of the profession to younger employees, and increased institutional legitimacy. These findings support the argument that AI is more likely to augment than entirely replace auditors. Automation can reduce the time devoted to document matching, routine testing, and repetitive verification, allowing auditors to focus on interpretation, risk analysis, systems evaluation, and professional judgment. Public-sector AI research similarly suggests that cognitive technologies can redesign work and enable employees to concentrate on higher-value responsibilities [22]. In this sense, intelligent auditing may enhance rather than diminish the strategic importance of the auditor.

The finding that AI adoption may increase institutional legitimacy is also significant. More timely, comprehensive, and transparent audits can strengthen public confidence and demonstrate that audit institutions are capable of responding to the complexity of digital governance. Institutional theory suggests that legitimacy is obtained when organizational practices are aligned with prevailing expectations and norms [17]. As digital transformation becomes increasingly associated with modernization and effective governance, the successful use of AI may enhance the credibility of public audit institutions. However, this legitimacy depends on responsible implementation. If AI is used without transparency, ethical safeguards, or reliable data, it may instead undermine trust.

Overall, the final model developed in this study demonstrates that AI adoption in public audit institutions is a socially negotiated, institutionally conditioned, and technologically dependent transition. Environmental pressures create the need for transformation, but organizational and institutional barriers shape how the process unfolds. Stepwise experimentation, proof of concept, interdisciplinary collaboration, and gradual role adaptation provide a practical means of navigating this transition. The model therefore extends previous research by integrating causal pressures, cultural and infrastructural barriers, action strategies, and professional and institutional consequences within a single grounded explanation.

This study has several limitations. First, the findings were derived from a qualitative sample of 15 participants and therefore reflect the experiences and interpretations of a specific group of senior managers, auditors, and information technology specialists. Although theoretical saturation was achieved, the findings cannot be statistically generalized to all public or private audit institutions. Second, the data were based on self-reported accounts and may have been influenced by participants' perceptions, professional interests, or concerns about discussing organizational weaknesses. Third, the study examined AI adoption at a particular stage of institutional development, and the identified categories may evolve as technologies, regulations, and professional practices change. Finally, the study focused primarily on organizational actors and did not directly incorporate the perspectives of regulators, audited entities, technology vendors, citizens, or professional associations.

Future studies should test and refine the proposed model across different institutional, national, and regulatory contexts. Comparative research could examine differences between public and private audit institutions, developed and developing economies, and institutions with varying levels of digital maturity. Quantitative studies may operationalize the categories identified in this research and evaluate the relationships among leadership commitment, data readiness, cultural resistance, governance clarity, implementation strategy, and adoption outcomes. Longitudinal research would be particularly valuable for tracing how pilot projects develop into institutionalized practices over time. Future studies should also examine the effects of AI adoption on audit quality, fraud detection, employee competencies, professional identity, public trust, and accountability.

Audit institutions should begin by assessing their technological, data, human-resource, and governance readiness before investing in large-scale AI systems. Managers should translate verbal support into clear budgets, implementation responsibilities, training programs, and measurable objectives. Institutions should prioritize data standardization, system integration, security, and quality assurance as prerequisites for AI adoption. Low-risk pilot projects should be used to demonstrate value and identify operational problems before wider deployment. Cross-functional teams involving auditors, managers, legal experts, and information technology specialists should guide implementation. Institutions should also establish clear rules for human oversight, algorithmic accountability, documentation, model validation, confidentiality, and responsibility for errors. Finally, workforce development should emphasize data literacy, analytical reasoning, ethical awareness, and the complementary relationship between professional judgment and intelligent technologies.

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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