Identifying Opportunities and Challenges of AI-Based Decision-Making in Auditing Using the Grounded Theory Method

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ABSTRACT

Artificial Intelligence (AI) is transforming auditing by enabling data-driven, efficient decision-making, yet its adoption faces significant challenges. This study employs a mixed-methods approach, integrating Grounded Theory, Fuzzy Delphi, and Analytic Hierarchy Process (AHP), to systematically investigate the opportunities and challenges of AI-based decision-making in auditing. Grounded in the Technology Acceptance Model (TAM) and Socio-Technical Systems (STS) theory, we conducted semi-structured interviews with 15 auditing experts, identifying six core constructs: skills and knowledge, implementation strategies, risk management, automated error detection, data interpretability, and big data analytics. These constructs were validated using Fuzzy Delphi and prioritized via AHP, with skills and knowledge rated highest (40.88% weight). The resulting framework provides actionable guidance for audit professionals, theoretical insights for researchers, and a roadmap for policymakers to navigate AI integration in auditing.

Keywords: Artificial Intelligence, Auditing, Decision-Making, Opportunities and Challenges, Grounded Theory

1. Introduction

The auditing profession is experiencing a profound transformation driven by Artificial Intelligence (AI), which enhances audit quality through automation, anomaly detection, and accelerated decision-making amid growing data complexity (Noordin et al., 2022). AI's capability to process vast datasets enables auditors to identify subtle patterns and irregularities, thereby improving reliability and efficiency. However, adoption is hindered by challenges such as algorithmic transparency, ethical considerations, legal accountability, and skill deficiencies among auditors (Losbichler & Lehner, 2021; Ferri et al., 2023).

Three critical research gaps persist: (1) a disconnect between AI's theoretical potential and its practical application in auditing, (2) limited empirical evidence capturing auditors' lived experiences, and (3) a scarcity of integrated frameworks combining qualitative and quantitative insights. This study addresses these gaps through a mixed-methods design, integrating Grounded Theory, Fuzzy Delphi, and Analytic Hierarchy Process (AHP) to develop a practitioner-validated framework for AI adoption in auditing.

Research Objectives

1. Identify and validate six core constructs shaping AI-based decision-making in auditing.
2. Enhance theoretical understanding by integrating TAM and STS frameworks.
3. Provide practical recommendations for audit firms, regulators, and educators.

Research Questions

Main Question: What comprehensive model best explains the opportunities and challenges of AI-based decision-making in the auditing process?

Sub-Questions:

1. What are the key components constituting the opportunities and challenges of AI-based decision-making in auditing?
2. How can these components be systematically measured and prioritized?

Literature Review

Global Perspectives

Global research underscores AI's transformative potential in auditing. Di Vaio et al. (2020) conducted a systematic review, identifying ethical, social, economic, and legal challenges in AI adoption, advocating for cultural shifts toward sustainability. Han et al. (2023) examined AI and blockchain integration, highlighting advancements like real-time auditing and triple-entry accounting. Fedyk et al. (2022) demonstrated AI's role in improving audit quality, while Lehner et al. (2022) identified five ethical challenges: objectivity, privacy, transparency, accountability, and reliability.

National Context

In Iran, AI adoption in auditing is gaining momentum. Khaleghizadeh Dehkordi et al. (2024) reported AI's positive impact on audit efficiency, particularly in investment analysis using machine learning models. Azad and Pourzamani (2022) emphasized AI's role in enhancing operational competitiveness through secure, automated auditing processes. Azarsaeed and Rostami (2023) explored ethical decision-making, identifying challenges like data privacy and algorithmic bias, and advocated for comprehensive skill development programs. Sadeghian et al. (2022) provided a detailed overview of AI technologies, including expert systems, neural networks, and fuzzy logic, in accounting and auditing. Mahdavi (2022) confirmed AI's integration into audit automation systems by major Iranian firms, signaling its institutionalization and growing acceptance.

Methodology

Research Population and Sampling

The study targeted auditors, financial managers, and university professors with at least ten years of auditing experience and a master's degree in accounting or auditing. Preference was given to Certified Public Accountants (CPAs) and academics at the Assistant Professor level or higher. Using purposive snowball sampling, 15 experts were recruited, achieving theoretical saturation (Guest et al., 2006). Table 1 summarizes participant demographics.

Table 1: Demographic Information of Respondents

No.	Gender	Position	Education	Auditing Experience (Years)
1	Male	Auditor	Ph.D. in Accounting	16
2	Male	Auditor	Master's in Accounting	32
3	Male	Financial Manager	Master's in Financial Management	29
4	Male	Auditor	Ph.D. Candidate in Accounting	23
5	Male	Head of Accounting	Master's in Accounting	19
6	Female	Auditor	Master's in Accounting	10
7	Female	Auditor	Master's in Accounting	12
8	Male	Auditor	Ph.D. in Accounting	16
9	Male	Financial Consultant	Ph.D. in Financial Engineering	16
10	Male	Financial Manager	Master's in Accounting	11
11	Male	Financial Consultant	Master's in Accounting	13
12	Male	Auditor	Master's in Accounting	10
13	Male	University Professor	Master's in Accounting	11
14	Male	University Professor	Master's in Accounting	17
15	Male	Financial Manager	Master's in Accounting	12

Data Collection

Semi-structured interviews, lasting 45–75 minutes, were conducted with 15 auditing professionals. Questions explored AI adoption opportunities, challenges, risks, and impacts on audit processes. Interview protocols included open-ended questions like: "What are the primary opportunities for AI in auditing?" and "What challenges hinder AI adoption?" Data collection ceased after theoretical saturation, confirmed through two additional interviews yielding no new insights.

Data Analysis

Grounded Theory, as outlined by Corbin and Strauss (2015), served as the cornerstone of the qualitative analysis, ensuring a systematic, inductive approach to theory development. The analysis proceeded through three coding stages:

1. **Open Coding**: Line-by-line analysis of interview transcripts identified initial codes, such as "AI training needs," "algorithmic bias," and "data complexity." Over 300 initial codes were generated, capturing diverse perspectives.
2. **Axial Coding**: Codes were grouped into categories based on their relationships, such as "organizational readiness" (encompassing training and resource allocation) and "technological barriers" (including interpretability and system integration). This stage reduced codes to 25 categories.
3. **Selective Coding**: A central theme, "AI readiness and adaptability in auditing," emerged, linking all categories and forming the basis of the proposed framework.

NVivo software facilitated systematic coding, ensuring traceability and consistency. To illustrate, codes like "lack of AI literacy" and "need for upskilling" were grouped under "skills and knowledge," while "data privacy" and "bias mitigation" formed the "risk management" category. Table 2 presents the resulting coding tree, detailing the six core constructs and their subcategories.

Table 2: Coding Tree for AI Adoption Constructs

Construct	Subcategory 1	Subcategory 2	Subcategory 3	Subcategory 4
Skills and Knowledge	AI Technical Competency	Data Science Expertise	Continuous Learning & Training	Change Management
Implementation Strategies	Planning and Roadmapping	Stakeholder Engagement	Iterative Deployment	Resource Allocation
Risk Management	Data Privacy Concerns	Algorithmic Bias	System Reliability	Regulatory Compliance
Automated Error Detection	AI-driven Anomaly Detection	Reduction of Manual Workload	False Positive Minimization	Alert System Effectiveness
Data Interpretability	Explainability of AI Outputs	Transparency in Decision-Making	Auditor Trust in AI	User-Friendly Interfaces
Big Data Analysis	Handling Volume and Variety	Advanced Analytical Techniques	Real-Time Data Processing	Integration with Legacy Systems

The Fuzzy Delphi Method, following Ishikawa et al. (1993), validated qualitative findings by achieving expert consensus on the six constructs. AHP, based on Saaty's (1980) methodology, prioritized constructs by assigning weights based on pairwise comparisons. Both methods ensured methodological rigor and alignment with qualitative insights.

Validity and Trustworthiness

Trustworthiness was ensured through:

- **Credibility**: Prolonged engagement with participants and member-checking of interview summaries.
- **Transferability**: Thick descriptions of the Iranian context and participant profiles.
- **Dependability**: Transparent coding processes documented via NVivo audit trails.
- **Confirmability**: Triangulation of qualitative (Grounded Theory) and quantitative (Fuzzy Delphi, AHP) data.

Snowball sampling bias was mitigated by recruiting participants from diverse roles (auditors, managers, academics). External validation via Fuzzy Delphi and AHP further enhanced robustness.

Interview Summaries

The 15 interviews provided rich insights into AI integration in auditing:

- **Expert 1 (Ph.D., Auditor)**: AI operates in three stages—intelligence (data organization), design (goal-setting), and choice (decision-making)—requiring auditors to master each.
- **Expert 2 (Auditor, 32 years)**: AI's dual nature offers opportunities with proper use but poses risks like bias with misuse.
- **Expert 3 (Financial Manager)**: Skill gaps necessitate targeted training in AI tools and data analytics.
- **Expert 4 (Ph.D. Candidate)**: Clear implementation strategies with feedback loops are critical for adoption.
- **Expert 5 (Head of Accounting)**: Neural networks enhance big data analysis and error detection efficiency.
- **Expert 6 (Female Auditor)**: Machine learning reduces risks by identifying patterns in complex datasets.
- **Expert 7 (Female Auditor)**: AI effectiveness hinges on auditors' technical and interpretive skills.
- **Expert 8 (Ph.D., Auditor)**: Risk management requires understanding threats, costs, and regulatory implications.
- **Expert 9 (Financial Consultant)**: Multi-dimensional implementation strategies align AI with organizational goals.
- **Expert 10 (Financial Manager)**: Automated error detection enhances audit credibility and efficiency.
- **Expert 11 (Financial Consultant)**: Data interpretability is vital for building trust in AI outputs.
- **Expert 12 (Auditor)**: Big data analytics requires robust classification and real-time processing capabilities.
- **Expert 13 (Professor)**: Continuous skill development is essential for AI-driven auditing.
- **Expert 14 (Professor)**: Implementation strategies must align with local technological resources.
- **Expert 15 (Financial Manager)**: AI strengthens internal controls but requires safeguards against collusion risks.

These summaries informed the Grounded Theory analysis, ensuring findings were rooted in practitioners' experiences.

Findings

Qualitative Insights

Grounded Theory analysis identified six constructs shaping AI adoption in auditing:

1. **Skills and Knowledge**: Auditors' proficiency in AI tools, data science, and change management is critical. For example, participants emphasized the need for training in Python and AI ethics to resolve errors and select appropriate tools.
2. **Implementation Strategies**: Phased roadmaps, stakeholder engagement, and iterative deployment enhance adoption. Participants highlighted the importance of pilot projects with feedback loops.

3. **Risk Management**: Protocols to mitigate biases, ensure data privacy, and comply with regulations are essential. Auditors noted concerns about algorithmic bias and system reliability.
4. **Automated Error Detection**: AI improves anomaly detection accuracy and reduces manual workload. However, false positives require careful calibration.
5. **Data Interpretability**: Transparent, explainable outputs foster trust and usability, addressing the “black box” issue of AI systems.
6. **Big Data Analysis**: Scalable platforms enable real-time, precise insights, though integration with legacy systems poses challenges.

Quantitative Prioritization

AHP prioritized constructs with consistency ratios (CR < 0.1), ensuring reliable pairwise comparisons. Fuzzy Delphi validated expert consensus using triangular fuzzy numbers, with thresholds for acceptance (average ≥ 0.85). Table 3 shows AHP weights, and Table 4 presents Fuzzy Delphi results.

Table 3: AHP Prioritization of Constructs

Criteria	Final Weight
Skills & Knowledge	0.4088
Implementation Strategies	0.2306
Risk Management	0.1328
Automated Error Detection	0.1237
Data Interpretability	0.0638
Big Data Analysis	0.0403

Table 4: Fuzzy Delphi Results

Component	L (Min)	M (Mean)	N (Max)	Final Average	Acceptance Status
Skills & Knowledge	0.90	1.00	1.00	0.967	Accepted
Implementation Strategies	0.88	0.99	1.00	0.953	Accepted
Risk Management	0.86	0.97	1.00	0.853	Accepted
Automated Error Detection	0.85	0.96	1.00	0.937	Accepted
Data Interpretability	0.85	0.96	1.00	0.937	Accepted
Big Data Analysis	0.85	0.96	1.00	0.937	Accepted

Discussion

Theoretical Integration

The findings align with TAM and STS theories. TAM posits that technology acceptance depends on perceived usefulness (e.g., error reduction, fraud detection) and ease of use (e.g., interpretability challenges) (Davis, 1989). For instance, automated error detection enhances perceived usefulness, while data interpretability improves ease of use. STS emphasizes balancing social (training, organizational readiness) and technical (infrastructure, tools) subsystems (Bostrom & Heinen, 1977). Skills and knowledge align with social subsystems, while big data analysis reflects technical requirements. Table 5 maps constructs to these theories.

Table 5: Mapping Constructs to TAM and STS

Construct	TAM (Usefulness/Ease of Use)	STS (Social/Technical)
Skills & Knowledge	Enhances ease of use via training	Social: Aligns human capabilities
Implementation Strategies	Increases usefulness via structured adoption	Technical: Ensures system alignment
Risk Management	Enhances usefulness by mitigating risks	Technical: Ensures reliability
Automated Error Detection	Increases usefulness via accuracy	Technical: Reduces manual errors
Data Interpretability	Improves ease of use via transparency	Social: Builds trust in AI outputs
Big Data Analysis	Enhances usefulness via real-time insights	Technical: Processes large datasets

Practical Implications

1. **Skills and Knowledge**: Develop competency matrices for Python, AI ethics, and prompt engineering, integrated into CPD programs. Example: A 12-week course on AI-driven auditing tools, including Power BI for data visualization and Python for data preprocessing.
2. **Implementation Strategies**: Pilot AI integration with ERP systems, using feedback loops. Example: A six-month pilot with cloud-based AI tools like SAP Analytics Cloud, incorporating stakeholder workshops.
3. **Risk Management**: Establish AI-specific risk committees to monitor biases and conduct stress tests. Example: Quarterly audits of AI outputs using Monte Carlo simulations to assess reliability.
4. **Automated Error Detection**: Use machine learning to flag anomalies. Example: Neural networks for real-time fraud detection in financial datasets, calibrated to minimize false positives.
5. **Data Interpretability**: Develop dashboards and explanatory notes. Example: Visual analytics platforms like Tableau or Power BI for transparent, user-friendly outputs.
6. **Big Data Analysis**: Deploy scalable cloud platforms. Example: AWS-based solutions for high-volume audit data, integrated with legacy systems via APIs.

Contextual Considerations

Iran's compliance-driven audit practices, shaped by stringent regulations under the Securities and Exchange Organization, and cultural skepticism toward automation (rooted in job security concerns), influence AI adoption. For instance, auditors prioritize risk management due to legal accountability, unlike India, where tech hubs drive rapid AI integration, or the U.S., with advanced regulatory frameworks. These differences necessitate tailored strategies, such as localized training programs and alignment with Iran's regulatory standards.

Conclusion

This study provides a robust, practitioner-validated framework for AI adoption in auditing, grounded in TAM and STS theories. Prioritizing skills and knowledge enables audit firms to maximize AI benefits, offering actionable guidance for practitioners and a foundation for future research.

Limitations and Future Research

Snowball sampling may overrepresent similar professional backgrounds, potentially skewing perspectives. Iran's unique regulatory environment, characterized by compliance-driven practices, and cultural attitudes, such as skepticism toward automation due to job security concerns, limit generalizability. For example, Iran's focus on risk management contrasts with India's emphasis on technological scalability or the U.S.'s focus on innovation. Future studies should employ mixed sampling methods (e.g., stratified random sampling) and conduct cross-country comparisons to enhance applicability across diverse contexts

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