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EXPLORING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN AUDITING USING SYSTEM DYNAMICS

Aarti Sethia*, Abhinav Pandey**

Abstract *Adoption of artificial intelligence (AI) in the auditing sector is influenced by ambiguous interaction of various factors that impact the input, processing, and output stages of AI adoption representing a complex system. System dynamics, one of the areas of system thinking, provides a comprehensive framework for understanding the dynamic behaviour and interactions of such complex systems. In the present research, the adoption of AI in auditing has been analysed through system dynamics. A conceptual framework of AI adoption has been proposed to comprehensively understand the process of AI adoption in auditing. Systems dynamics tools such as causal loop diagram (CLD) and stock and flow diagram have been deployed to study the complex and unclear interactions of factors influencing adoption. To simulate and model AI adoption in auditing, Vensim and Stella software were utilised to construct a CLD and a stock and flow model, offering novel understandings into the drivers and inhibitors of AI integration. This study provides a foundational understanding for practitioners and researchers navigating the transformative impact of AI on auditing.*

Keywords: *Artificial Intelligence, Auditing, System Dynamics, Causal Loop Diagram, Stock Flow Model*

INTRODUCTION

Artificial Intelligence

Artificial intelligence (AI) is a field of study dedicated to developing systems that can simulate human intelligence using computer systems and enable them to perform cognitive functions such as learning, reasoning, problem solving, and decision making (Davenport & Ronanki, 2018). AI's unique capability lies in its ability to learn from data, adapt to new inputs, and carry out tasks with increasing accuracy without requiring explicit programming through various data-driven technologies such as machine learning (ML), which enables computers to learn from experience and improve their performance over time (Surden, 2021); deep learning, a specialised branch of ML that utilises neural networks to process complex datasets, such as images and speech recognition, mimicking the structure of the human brain (Aggarwal et al., 2022); artificial neural networks, which are a paradigm for information processing inspired by biological nervous systems, including the brain (Dongare et al., 2012); and robotics, which involves the development of machines called robots that can replicate or substitute human actions (Webster, 2020). These concepts collectively differentiate AI from conventional software (Jamal et al., 2020). Traditional definitions by early AI pioneers emphasise the replication of human cognitive abilities. McCarthy (1956) initially defined AI as the ability of machines to imitate human intelligence as accurately as possible (Cordeschi, 2007). This fundamental principle emphasises that AI aims to emulate the cognitive behaviours often linked to humans. Rich and Knight (1991) provide a conventional definition that further elucidates this concept. AI is defined as "actions by machines that would be deemed intelligent if executed by a human". Haenlein and Kaplan (2019, as referenced in Zemánková, 2019) provide a functional definition, characterising AI as a system that comprehends, learns from, and adapts external inputs to achieve certain goals. This corresponds with Zhang et al. (2020), who characterise AI as a data-intensive technology that utilises big data and ML to extract insights from historical data and generate predictions.

* Research Scholar, Department of Management, Faculty of Social Sciences, Dayalbagh Educational Institute (DEI), Agra, Uttar Pradesh, India. Email: aarti141520@dei.ac.in

** Assistant Professor, Department of Management, Faculty of Social Sciences, Dayalbagh Educational Institute (DEI), Agra, Uttar Pradesh, India. Email: abhinavpandey@dei.ac.in

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Programming-oriented definitions see AI as a technology framework for adaptive decision making. Issa et al. (2016) provide a functional view on AI, defining it as a "computer program capable of making balanced decisions, observing its environment, and performing actions that enhance its probability of achieving a goal". This presents the concept of AI systems that can adapt and make judgements depending on external inputs, transitioning AI from mere task automation to dynamic decision-making processes. Lu, Li, Chen, Kim and Serikawa (2018) expand the term to include activities that allow robots to do jobs usually performed by humans. This encompasses progress in expert systems, pattern recognition, ML, and computational reasoning.

Adoption of AI in Auditing Practices

Auditing is a systematic process of analysing and investigating the uniformity of financial reports and statements to determine whether they accurately and completely reflect financial transactions (Lombardi et al., 2014). The International Auditing Practice Committee (IAPC) defines auditing as "the independent examination of financial information of any entity, whether profit-oriented or not, and regardless of its size or legal form, when such an examination is conducted with the view of expressing an opinion on it". However, over time, auditing has evolved significantly, expanding beyond mere financial assessments to encompass operational evaluation (Gupta et al., 2011). This expansion is driven by the increasing complexity of financial transactions, evolving regulatory landscapes, and heightened stakeholder expectations. The dynamic business environment and increasingly stringent regulatory requirements have necessitated significant advancements in audit practices, leading to the integration of advanced technologies such as AI, which enhances auditing through automation, error minimisation, and sophisticated fraud detection (Fedyk et al., 2022). AI-powered big data analytics enable auditors to examine extensive datasets, thereby improving assurance and audit effectiveness (Anh et al., 2024). Furthermore, AI-driven risk assessment enhances auditors' capacity to manage large datasets, identify patterns, detect potential risks, and uncover control gaps, facilitating more strategic allocation of audit efforts (Odeyemi et al., 2024). Another critical application of AI in auditing is fraud detection and identification of potentially fraudulent activities for further investigation, thus mitigating financial risks for organisations (Adelakun et al., 2024). The automation of routine audit tasks, such as documentation, reconciliation, and data entry, streamlines audit processes and allows auditors to focus on more strategic and analytical tasks (Igou et al., 2023). AI also enables continuous, real-time monitoring of financial transactions, provides auditors with immediate insights into an organisation's financial health, and enhances reporting by generating comprehensive and insightful audit reports that highlight key findings and suggest areas for improvement (Srinivas, 2024).

These procedures are implemented through different AI tools such as ML, which is employed for pattern detection and risk prediction (Akinadewo et al., 2023); natural language processing (NLP), which is used for information extraction (Supriadi, 2024); robotic process automation (RPA), which facilitates task automation (Zhang et al., 2020); and cognitive automation, which integrates ML, NLP, and RPA, and is applied for complex data analysis and generating insights (Srinivas, 2024).

In light of the above facts, these AI-driven advancements in auditing not only improve operational efficiency but also enable auditors to shift their focus to higher-value tasks such as critical analysis and advisory services, ultimately strengthening the overall audit process (Baldwin et al., 2020).

System Dynamics: A Tool for Understanding Adoption of AI in Auditing Practices

System dynamics is a tool for understanding and modelling the behaviour of complex systems over time (Bala et al., 2017). It utilises feedback loops, time delays, and stock and flow diagrams to represent the dynamic relationships between various components within a system (Sterman, 2000). By constructing computer simulations, system dynamics allows researchers to explore how these interactions lead to emergent behaviours and long-term trends, often uncovering unintended consequences and identifying leverage points for intervention.

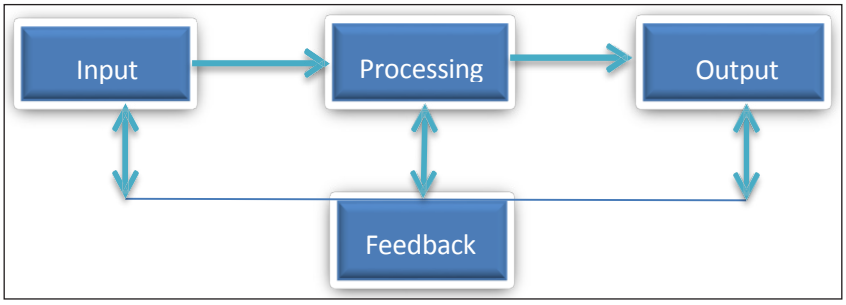
The current paper conceptualises the adoption of AI in auditing as a complex system, structured around three main stages: input, processing, and output. These stages integrate the key enabling factors, challenges, and outcomes reflecting the dynamic interactions between macro-level factors such as regulatory and ethical concerns and micro-level processes like audit planning and execution.

In the input stage, the focus is on gathering and structuring the necessary resources, technologies, and knowledge for AI implementation in auditing. Technological infrastructure plays a critical role here, including robust data management systems for storage, integrity, and security for AI-based tools (Luthfiani, 2024). The processing stage focuses on AI implementation and adoption, addressing the dynamic interactions between technology, human factors, and process complexities. Designing and training AI systems requires the

development and customisation of algorithms for specific audit functions such as risk assessment, anomaly detection, and financial statement analysis (Almaqtari et al., 2024).

The output stage focuses on the results of AI adoption, highlighting the balance between technological improvements and professional standards. AI adoption can significantly increase audit efficiency by automating routine tasks such as data extraction, validation, and reconciliation (Odonkor et al., 2024).

Finally, the feedback process in AI implementation for auditing is a continuous, iterative loop aimed at enhancing performance, ensuring accuracy, and aligning outcomes with organisational goals and professional standards.



Source: Author's own construct.

Fig. 1: Adoption of AI in Auditing Practices Represents a System

Therefore, to understand the complex nature of AI adoption in auditing practices, researchers employ system dynamics, as it allows for an in-depth examination of the causal relationships, feedback loops, and time delays that shape system behaviour. This holistic approach facilitates the exploration of the dynamic behaviour of AI integration, ultimately informing better decision making and enabling more effective management of AI's transformative effects within the auditing landscape.

LITERATURE REVIEW

AI has been increasingly integrated into auditing practices, offering remarkable capabilities to improve audit accuracy, fraud detection, and operational efficiency. The literature review on the adoption of AI in auditing demonstrates substantial progress in understanding the adoption and execution of AI technologies in the audit profession. Early research by Baldwin et al. (2006) recognised AI's significant role in analytical reviews, risk assessments, and fraud detection. Further studies by Rosil (2012, 2013) and Omoteso (2012) highlighted AI's potential to automate audit processes and improve anomaly detection.

Kokina and Davenport (2017) described AI as a disruptive force in data-intensive audits, exemplified by tools such as IBM Watson and PwC's Halo platform. Davenport and Ronanki (2018) argued that AI adoption should focus on enhancing business capabilities, while Tiberius et al. (2019) noted its potential in predictive analytics and continuous auditing. The Technology-Organisation-Environment (TOE) framework has been used by Seethamraju et al. (2020) and Handoko (2021) to assess factors impacting AI adoption in auditing, including technological complexity and organisational readiness. Simina and Dutescu (2024) also apply the TOE framework to AI adoption in auditing, identifying technological compatibility, security, and complexity as key factors. Organisational support and regulatory pressures also influence AI integration. Adelakun et al. (2024) highlight AI's role in fraud detection and risk management, while Odeyemi et al. (2024) discuss AI's broader impact on real-time auditing and compliance monitoring, stressing the importance of balancing AI adoption with ethical considerations.

In addition, several studies emphasise the systems approach, particularly within organisational contexts, using a comprehensive perspective to oversee intricate operations. Andruetto et al. (2024) use system dynamics in their study to elucidate the dynamics and processes associated with the obstacles and opportunities of city hub implementation. The working paper by Sterman (2002) emphasises the need of merging system dynamics with a comprehensive knowledge of human systems to successfully address policy opposition and promote sustainable advancements in complex contexts. In her work, Chechvala (2024) underscores the need of adopting systems thinking in management practices to successfully address wicked challenges, emphasising stakeholder participation and methodological variety as essential elements for success. The study by Laimon et al. (2022) offers an extensive examination of the Australian energy industry using systems thinking. The authors underscore the need of a systems-thinking methodology to comprehend the intricacies of the energy industry.

This methodology facilitates the identification of interconnections across diverse subsystems and their long-term dynamics, which conventional linear reasoning does not adequately handle (Laimon et al., 2022). Sushil (2018) examines the development and use of systems approach in research, especially within the management field.

Table 1: Synthesis Matrix of Literature Review

Title	Category	Focus Issue				Context		Data Type		Methodology		
		Author(s) (Year)	Artificial Intelligence	Adoption Theories	Systems Approach	Indian	Foreign	Qualitative	Quantitative	Exploratory	Descriptive	Analytical
Factors Influencing Audit Technology Acceptance by Audit Firms: A New I-TOE Adoption Framework Khairina Rosli (2012)	Research Article	✓		✓			✓	✓			✓	
The application of artificial intelligence in auditing: Looking back to the future Kamil Omoteso (2012)	Research Paper	✓	✓				✓	✓			✓	
Adoption of Audit Technology in Audit Firms Khairina Rosli (2013)	Conference Paper	✓	✓				✓		✓			✓
The Emergence of Artificial Intelligence: How Automation is Changing Auditing Kokina et al. (2017)	Research Article	✓	✓				✓	✓			✓	
Impacts of Digitization on Auditing: A Delphi Study for Germany Victor Tiberius et al. (2019)	Research Article	✓	✓				✓	✓				✓
Robot Human Interaction: Role of Artificial Intelligence in Accounting and Auditing Om Prakash Gusai (2019)	Research Article	✓	✓			✓		✓				✓

Summary of Literature Review												
Title Author(s) (Year)	Category	Focus Issue				Context		Data Type		Methodology		
		Auditing	Artificial Intelligence	Adoption Theories	Systems Approach	Indian	Foreign	Qualitative	Quantitative	Exploratory	Descriptive	Analytical
Factors Inhibiting the Adoption of Artificial Intelligence at organizational-level: A Preliminary Investigation Sulaiman Alsheiabni (2019)	Research Paper		✓	✓			✓		✓			✓
How Artificial Intelligence Changes the Future of Accounting Industry Mohammad et al. (2020)	Research Article		✓				✓	✓			✓	
Adopting AI in Organizational Decision Making A qualitative study Ludwig Entzenberg (2020)	Thesis		✓				✓		✓		✓	

Summary of Literature Review													
Title Author(s) (Year)	**Category**	**Focus Issue**				**Context**		**Data Type**		**Methodology**			
		Auditing	**Artificial Intelligence**	**Adoption Theories**	**Systems Approach**	**Indian**	**Foreign**	**Qualitative**	**Quantitative**	**Exploratory**	**Descriptive**	**Analytical**
Big Data Analytics and Other Emerging Technologies: The Impact on the Australian Audit and Assurance Profession Michael Kend et al. (2020)	Research Paper	✓	✓	✓			✓	✓		✓		
Identifying Key Factors for Adopting Artificial Intelligence-Enabled Auditing Techniques by Joint Utilization of FUZZY-ROUGH SET Theory and MRDM Technique Kuang-Hua Hu et al. (2020)	Research Paper	✓	✓				✓		✓			✓
Factors Influencing the Adoption of Artificial Intelligence in Organizations – From an Employee's Perspective Sai Ambati et al. (2020)	Research Article		✓	✓			✓	✓		✓		
The Impact of Artificial Intelligence and Blockchain on the Accounting Profession Zhang et al. (2020)	Research Paper		✓				✓	✓			✓	
How Audit Firm Size Moderate Effect of TOE Context Towards Auditor Adoption of Machine Learning Bambang Leo Handoko (2021)	Research Paper	✓	✓	✓			✓		✓			✓
The effect of artificial intelligence technologies on audit evidence Saleh Mohammed (2021)	Research Article	✓	✓				✓		✓		✓	✓
Reciprocal Use of Artificial Intelligence in Audit Assignments Gultom, Juan Barus (2021)	Research Paper	✓	✓				✓		✓			✓
The Use of AI in Auditing Practice: A Study of the Adoption at the Firm Level Jiaqi (Jack) Yang (2021)	Thesis	✓	✓	✓			✓	✓		✓		
Adoption of AI in the Auditing Practice: A Case study of a Big Four Adoption of AI in the Auditing Practice: A Case study of a Big Four Accounting Firm Jiaqi Yang et al. (2021)	Research Article	✓	✓	✓			✓	✓		✓		
The Adoption Of Artificial Intelligence in Human Resource Management Bilal Hamoud (2021)	Research Paper		✓	✓			✓		✓			✓
Exploring artificial intelligence adoption in public organizations: A comparative case study Oliver Neumann et al. (2022)	Research Paper		✓	✓			✓	✓		✓		✓

Summary of Literature Review												
Title Author(s) (Year)	Category	Focus Issue				Context		Data Type		Methodology		
		Auditing	Artificial Intelligence	Adoption Theories	Systems Approach	Indian	Foreign	Qualitative	Quantitative	Exploratory	Descriptive	Analytical
Artificial intelligence and auditing in small- and medium-sized firms: Expectations and applications P. Rikhardsson et al. (2022)	Research Article	✓	✓	✓			✓	✓		✓		
Artificial Intelligence (AI) in Accounting & Auditing: A Literature Review Ahmed Rizvan Hasan (2022)	Review Article	✓	✓				✓	✓			✓	
Critical Factors Affecting the Adoption of Artificial Intelligence: An Empirical Study in Vietnam Thanh Luan Nguyen et al.(2022)	Research Article	✓	✓				✓		✓			✓
A Survey of Artificial Intelligence Challenges: Analyzing the Definitions, Relationships, and Evolutions Saghiri et al. (2022)	Review Article		✓				✓	✓			✓	
In What Way Does Artificial Intelligence Influences Audit Practice? Empirical Evidence from Southwest, Nigeria Israel S. Akinadewo et al. (2023)	Research Paper	✓	✓				✓		✓			✓
Impact of Artificial Intelligence on Accounting, Auditing and Financial Reporting Ke-afoon Collins Kindzeka (2023)	Research Article	✓	✓				✓	✓			✓	
Artificial Intelligence: Definition and Background H Sheikh et.al. (2023)	Research Paper		✓				✓	✓			✓	
The impact of artificial intelligence on audit profession Luis Rodrigues et al. (2023)	Research Article	✓	✓				✓	✓			✓	
An Interpretive Structural Modelling for Studying the Effect of E-Consumer Behaviour on Company's Value Chain. Abinav Pandey et al. (2023)	Research Paper			✓	✓	✓		✓		✓		
Systems Thinking Applied to Higher Education Curricula Development Reza Rahdar et al. (2023)	Research Article				✓		✓	✓			✓	
A Complex Adaptive System Approach for the Water- Energy-Food Security Nexus Afreen Siddiqi (2023)	Research Article				✓		✓	✓			✓	
Systems thinking for management practitioners and scholars: Strengthening the tools to analyze "wicked problems" Sarah Cechvala (2024)	Research Article				✓		✓	✓			✓	

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Title Author(s) (Year)	**Category**	**Focus Issue**				**Context**		**Data Type**		**Methodology**			
		Auditing	**Artificial Intelligence**	**Adoption Theories**	**Systems Approach**	**Indian**	**Foreign**	**Qualitative**	**Quantitative**	**Exploratory**	**Descriptive**	**Analytical**
TOE framework elements used on Artificial Intelligence implementation in the accounting and audit sector Mihai Mirela Simina et al. (2024)	Research Article	✓	✓	✓			✓	✓			✓	
An ISM-MICMAC Based Approach to Analyze Cloud Computing Adoption in Organizations Abhinav Pandey et al. (2024)	Research Paper			✓	✓	✓		✓		✓		
The role of AI in transforming auditing practices: A global perspective review Olubusola Odeyemi et al. (2024)	Review Article	✓	✓				✓	✓			✓	
The impact of AI on accounting practices: A review: Exploring how artificial intelligence is transforming traditional accounting methods and financial reporting Beryl Odonkor et al. (2024)	Review Article	✓	✓				✓	✓			✓	
The impact of artificial intelligence on information audit usage: Evidence from developing countries Faozi A. Almaqtari et al. (2024)	Research Article	✓	✓	✓			✓		✓			✓
Exploring Factors Influencing the Adoption of AI Tools in Auditing: A Mixed-Methods Study Fahad Alsudairi (2024)	Dissertation	✓	✓	✓			✓	✓	✓		✓	✓
The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices Abdulwahid Ahmad et al. (2024)	Research Article	✓	✓	✓			✓		✓			✓
The Artificial Intelligence Revolution in Accounting and Auditing: Opportunities, Challenges, and Future Research Directions Anin Dyah Luthfiani et al. (2024)	Research Article	✓	✓	✓			✓		✓			✓
Digital Transformation and Artificial IntelligenceAssisted Auditing: The Role of Technology in Internal Audit Processes in 2025 Gökoğlan et al. (2025)	Research Article	✓	✓				✓	✓			✓	

Source: Formulated by the researcher based on existing studies.

RESEARCH GAP

Artificial intelligence (AI) adoption in auditing practices has been explored in numerous studies. However, despite the growing body of literature, there remains a critical gap: the absence of a holistic, systems dynamics-based approach that thoroughly examines the integration of AI in auditing. Existing research often focus on individual factors such as technological capabilities, organisational readiness, or regulatory pressures, without considering how these elements interact over time in a dynamic, interconnected system. This perspective fails to capture the complexity of AI adoption in auditing, where feedback loops, delays, and nonlinear relationships play a critical role.

A systems dynamics-based approach provides a more comprehensive framework, allowing researchers to model how different factors such as organisational culture, regulatory changes, and market competition interact to influence AI adoption. This approach also helps identify feedback loops, such as how the initial resistance to AI may decrease as organisations improve their AI capabilities or how regulatory shifts might impact adoption timelines.

This study fills the gap by applying a systems dynamics lens to AI adoption in auditing, offering insights into the dynamic processes that influence successful integration. The findings will contribute to both academic discourse and practical strategies for implementing AI technologies in a sustainable and scalable manner within the auditing profession.

RESEARCH METHODOLOGY

Research Design and Sampling Technique

The research is exploratory in nature since it employs a systems approach and it utilises a non-probability sampling technique.

Research Objectives

The purpose of this proposed research is to address the following objectives:

Objective 1: To propose a conceptual framework for adoption of AI in auditing practices.

Objective 2: To develop a causal loop diagram to know the dynamic interaction between different variables.

Objective 3: To simulate the market dynamics of AI adoption in auditing practices through stock and flow diagram.

Data Collection

The study utilised both primary and secondary data. Primary data were collected through a Likert-scale (1–5) questionnaire to elicit expert opinions on key factors influencing AI adoption, which were subsequently used to develop the system dynamics model. Secondary data were collected from diverse sources, including reports, journal publications, articles, blogs, newspapers, and research papers published in reputable national and international journals, as well as credible online resources.

Sampling Plan

The participants were drawn from various domains, including academic, professional, and industry sectors. A brief classification of experts is provided below:

Table 2: Sampling Plan

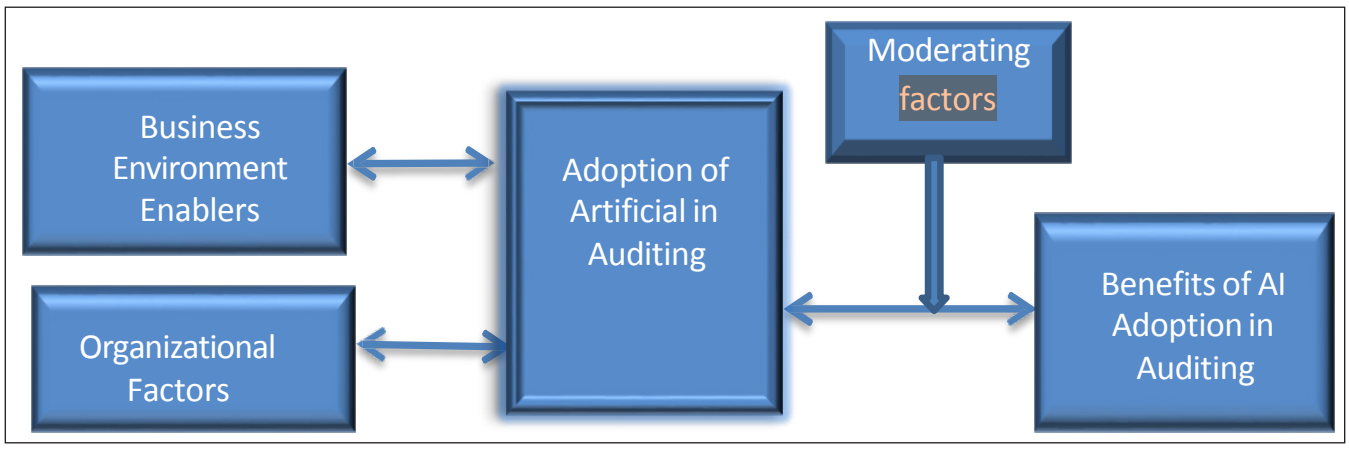
Domain Experts (AI & Auditing)	Academicians (Accounting & IT)	Auditors (Internal and External)	Audit Firm Managers	Representatives from Professional Bodies	Total Participants
3–5	2–4	3–4	2–3	2–3	10–15

Source: Author's own construct.

FINDINGS AND ANALYSIS

The first objective of this research is to establish a robust conceptual framework for AI adoption in auditing practices. The framework was developed on an I-P-O model analysis that offers a structured perspective on AI integration. The conceptual framework was constructed by employing two technology adoption theories: technology, organisational, and environmental (TOE) theory and diffusion of innovation (DOI) theory. The TOE framework, comprising technological, organisational, and environmental factors, provides a comprehensive lens through which AI adoption can be examined. Technological factors, such as AI's inherent benefits; scalability, accuracy, efficiency, trust, and reliability,

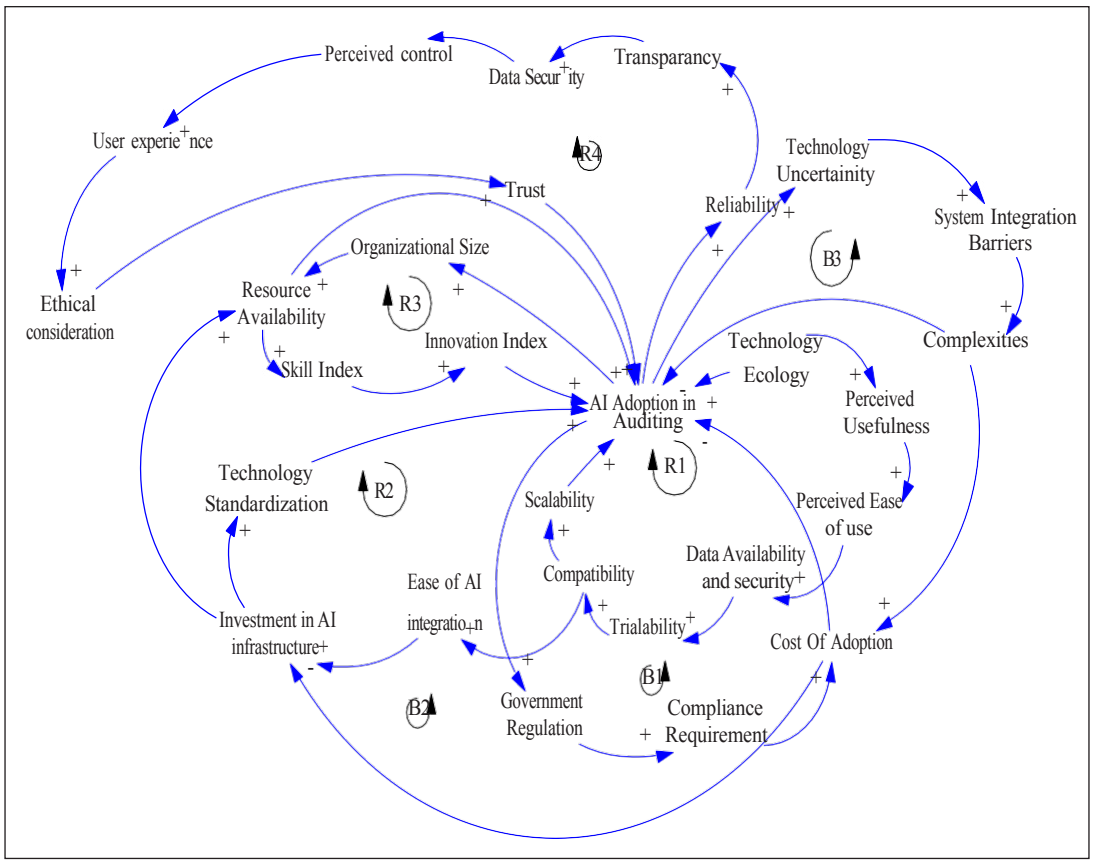
significantly influence adoption decisions within the auditing context. Organisational factors, reflecting internal readiness, encompass elements such as top management support, employee skillsets, and the organisation's capacity to manage workflow changes and provide AI training. Environmental factors representing external pressures include competitive forces, regulatory demands, market trends, technological ecosystems, cost efficiency, and market reach. The cost efficiency and competitive advantage offered by AI-driven auditing can be powerful drivers of adoption. Complementing the TOE framework, the DOI theory, which focuses on the diffusion of innovations within a population, is utilised to evaluate AI adoption in auditing. The DOI theory outlines five key factors that influence adoption decision such as the relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). These two theoretical frameworks were integrated to delineate two categories of factors: enablers and moderators. Enablers actively promote and facilitate AI adoption by providing the necessary environment, resources, and incentives for integration into audit workflows. Both internal and external factors serve as enablers. Internally, organisations must assess their readiness, employee competencies, and management support. Externally, market competition and regulatory changes may necessitate adoption. These internal and external factors, aligned with the TOE framework, are incorporated within the proposed model through the fundamental constructs of business environment enablers and organisational factors. The moderating factors that influence the rate and success of AI adoption are closely aligned with the DOI theory. By either facilitating or hindering adoption, these factors are crucial in determining the efficacy and efficiency of AI implementation in auditing. The perceived benefits of AI, including scalability, accuracy, and efficiency, coupled with its relative advantages over traditional methods, significantly influence the rate and effectiveness of AI adoption by auditing firms. Consequently, this integrated conceptual framework provides a comprehensive and nuanced understanding of the factors driving AI adoption in the auditing practices.



Source: Author's own construct.

Fig. 2: Conceptual Framework

The next objective of the study is to analyse the contextual relationship between the factors that affect AI adoption in auditing practices. To achieve this, a Causal Loop Diagram has been created, which includes four reinforcing loops and three balancing loops, as shown below:



Source: Developed by the researcher.

Fig. 3: Causal loop Diagram of Adoption of Artificial Intelligence in Auditing

R1 represents the reinforcing effect of AI adoption in auditing practices; as for the adoption of AI technology ecology plays an important role. Strong technology ecology, characterised by well-integrated systems and readily available infrastructure, directly influences the perceived usefulness of AI, making AI solutions more attractive for auditors. When AI is seen as beneficial, it positively influences perceived ease of use, encouraging users to engage with the technology (Venkatesh & Davis, 2000). A higher ease of use leads to better data availability and security, ensuring reliable data management (Al-Htaybat & von Alberti-Alhtaybat, 2017). Secure data fosters trialability, allowing organisations to experiment with AI before full implementation (Rogers, 2003), which in turn increases compatibility with existing systems. Greater compatibility enhances scalability, enabling AI to be deployed across different auditing functions, ultimately reinforcing AI adoption (Issa et al., 2016).

When AI systems are compatible and designed to seamlessly align with existing auditing workflows, the ease of integration increases, minimising disruptions to operational processes. This smooth integration fosters greater investment in AI infrastructure, as organisations recognise the potential for efficiency gains and risk reduction, and this leads to greater technology standardisation, which minimises interoperability challenges and promotes more widespread AI adoption across the industry (R2).

R3 shows the impact of organisational size on AI adoption, as larger organisations typically have greater resource availability, including financial capital, infrastructure, and workforce capabilities, which facilitate the adoption of emerging technologies. Increased resources contribute to a higher skill index, as organisations can invest in employee training, talent acquisition, and advanced technological expertise, thereby enhancing the workforce's ability to integrate AI effectively (Issa, Sun, & Vasarhelyi, 2016). In addition, resource abundance fosters an innovation-driven culture, reflected in a higher innovation index, where organisations actively experiment with and implement AI solutions to optimise their auditing processes. As AI

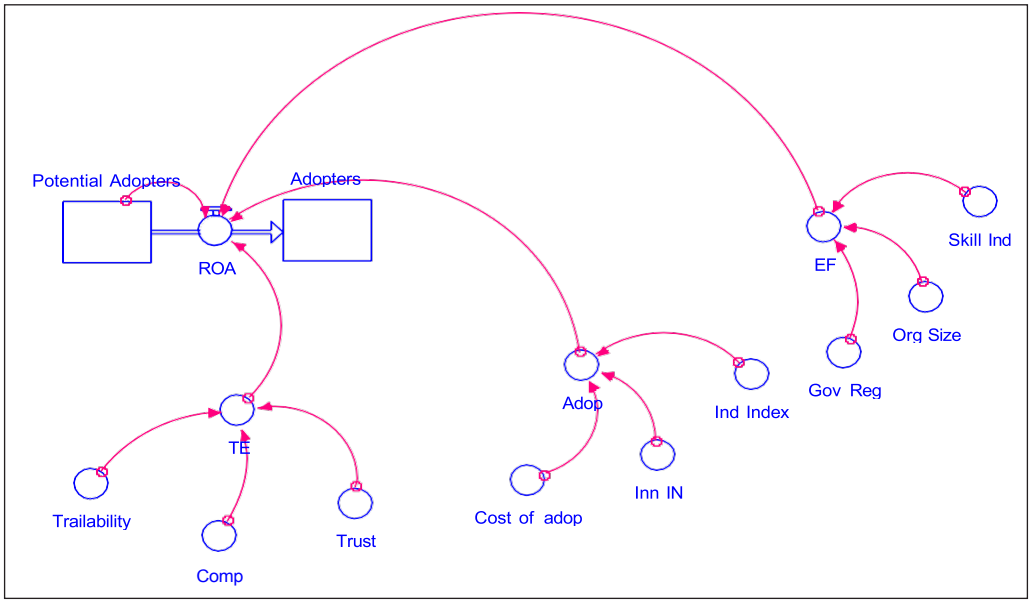
adoption becomes more widespread, it enhances operational efficiency, decision making, and competitive advantage, ultimately contributing to further organisational growth.

R4 emphasises the importance of reliability in building trust and promoting ethical AI adoption. AI systems that demonstrate high reliability enhance transparency in auditing processes, improving data security and strengthening perceived control over AI-generated insights. This enhanced control contributes to a better user experience, encouraging auditors to embrace AI solutions more readily. A positive user experience fosters ethical considerations, ensuring that AI is deployed responsibly and in accordance with relevant regulatory standards (Al-Htaybat et al., 2017). This commitment to ethical AI practices further drives AI adoption, which, in turn, can lead to improvements in system reliability, creating a positive feedback loop of continuous improvement and trust.

The CLD additionally comprises three balancing loops that show the constraints and challenges associated with AI adoption. B1 focuses on the regulatory and cost-related barriers. As AI becomes more prevalent in auditing, regulatory bodies are likely to impose stricter regulations to ensure ethical use, data security, and compliance. These increased compliance demands drive up the costs of AI adoption, potentially making it financially challenging for some firms to implement AI-driven auditing solutions. These higher costs can slow down adoption, and the time lag often associated with regulatory changes can further complicate AI deployment strategies. Integrating AI into established auditing practices introduces significant technological and operational complexities, which can significantly increase the overall cost of adoption. These higher costs can discourage firms from investing in necessary AI infrastructure, leading to reduced resource availability and a slowdown in AI integration. Furthermore, the time delay between initial investment and the realisation of AI's full potential can lead organisations to hesitate in expanding their AI adoption efforts, thereby limiting its overall impact on auditing processes (B2). Finally, B3 highlights how technology uncertainty can hinder AI adoption. As AI technologies continue to evolve rapidly, concerns regarding system compatibility, long-term sustainability, and future regulatory compliance can create significant system integration barriers (Issa et al., 2016). These integration challenges increase complexity, making AI adoption more difficult and resource-intensive. This increased complexity can discourage firms from expanding their AI initiatives, leading to a slowdown in overall adoption.

Thus, these reinforcing and balancing feedback loops show the interconnected dynamics of AI adoption in auditing practices. While reinforcing loops highlight the potential for rapid integration and advancement, balancing loops emphasise the critical need to address regulatory concerns, manage implementation complexities, and mitigate technology uncertainty.

The next objective was to simulate the market dynamics of AI adoption in auditing practices. To achieve this, researchers have constructed a stock and flow model using Stella software based on the principles of the Bass Model.



Source: Author's own construct.

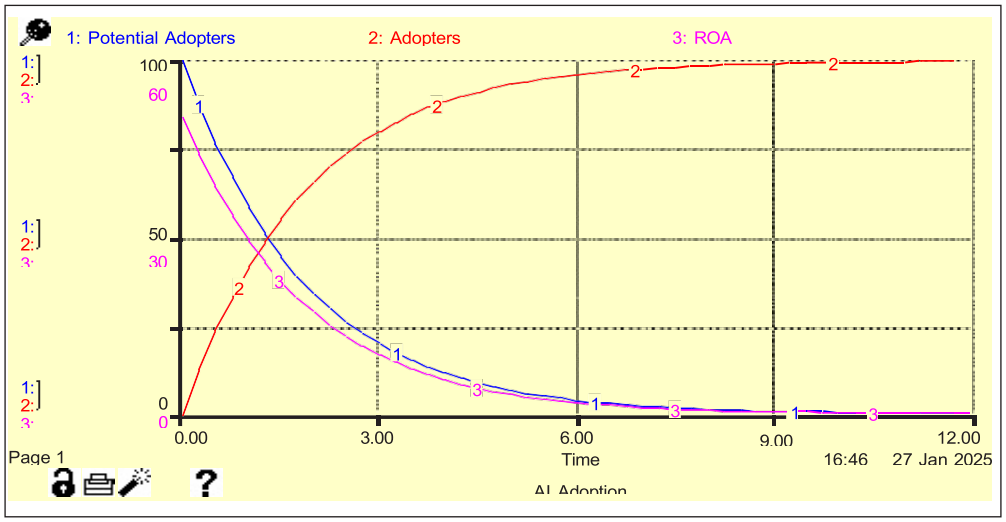
Fig. 4: Stock and Flow Diagram of Adoption of Artificial Intelligence in Auditing

The two stock variables are potential adopters and adopters. Potential adopters represent those firms that recognise the transformative potential of AI in auditing and view technological advancement as a key factor in achieving sustained competitive advantage. Adopters are technologically progressive firms that seek to optimise operational efficiency, enhance audit quality, and gain strategic insights through AI-driven tools.

The rate at which potential adopters transition to adopters is termed as ROA (rate of adopters). This adoption rate is influenced by key auxiliary variables that define the current AI adoption landscape in auditing. The researcher has captured these market variables through factors such as trialability, compatibility (comp), and trust. Trialability refers to the extent to which AI solutions can be experimented with before full-scale implementation, which can accelerate adoption by reducing uncertainty. Compatibility reflects the degree to which AI integrates with existing systems and processes, influencing ease of adoption. Trust is crucial, as confidence in the technology and its outcomes affects decision making in organisations. TE, an acronym developed by the researcher, captures the effect of these auxiliary variables on the rate of flow from potential adopters to actual adopters.

Another key factor affecting adoption is the cost of adoption. High costs may create barriers, whereas lower costs may facilitate quicker implementation. The stock and flow model also includes innovation index (Inn In) and industry index (Ind In) as influential variables. The Inn In captures the overall innovation climate within an industry, indicating how receptive firms are to adopting new technologies. The Ind In likely reflects sectoral characteristics that influence adoption rates, such as regulatory constraints or market competition. The researcher has coined the term ADOP to capture the effect of the above-stated variables on AI adoption.

The external environment plays a crucial role in adoption, represented by environmental factors (EF). This category includes government regulations (Gov Reg), organisational size (Org Size), and skill index (SI). Government regulations can either encourage or hinder adoption, depending on policy incentives, legal requirements, and compliance costs. Organisational size influences adoption capabilities, as larger firms may have more resources to invest in AI. The skill index reflects the availability of a skilled workforce, which is a critical enabler of AI implementation.



Source: Simulation output developed by authors using Stella software.

Fig. 5: Simulation of System Dynamic Model

The simulation graph clearly shows that, over time, all potential adopters in the auditing sector will incorporate AI into their practices. As a result, the stock variable representing potential adopters (the blue line) gradually declines towards zero. The adoption rate of AI in auditing follows an S-curve pattern, which indicates an initial slow uptake, followed by rapid adoption, and eventually reaching saturation as most firms implement AI solutions. The ROA, represented by the third curve, indicates the speed at which this adoption occurs. The ROA begins high as adoption is most rapid early in the process but gradually decreases as fewer potential adopters remain.

Hence, the graph demonstrates a typical adoption lifecycle, where the number of potential adopters diminishes over time as the number of actual adopters increases, and the rate of

adoption slows as the process nears completion. This reflects the natural progression of technology adoption, where early enthusiasm drives rapid adoption, eventually tapering off as the majority of the population has adopted the technology.

CONCLUSION

The present study advances a novel integrative modelling paradigm for the adoption of AI in auditing practices. This research has successfully developed and analysed a conceptual framework that sheds light on the critical factors influencing AI adoption in auditing practices. Through the application of causal loop diagrams, the researchers have demonstrated the complex, dynamic relationships between technological, organisational, and environmental elements. The stock and flow diagram was further used to simulate the market dynamics of AI adoption using Stella software, offering practical implications for auditing firms seeking to strategically implement AI. The validated framework, including CLDs and stock and flow diagrams, supported by expert insights and a thorough literature review, provides a robust foundation for future research and underscores the need for a holistic and dynamic understanding of various factors to ensure successful AI integration and drive innovation in the auditing sector.

IMPLICATIONS

This research contributes notably to both academia and practice by adopting a system dynamics approach to understanding AI adoption in the auditing sector. The study moves beyond traditional linear models, presenting AI adoption as a complex system influenced by interrelated technological, organisational, and environmental factors.

Theoretically, the study enriches AI adoption literature by framing it within systems thinking, offering a replicable conceptual framework for future research. Methodologically, it introduces, a robust modelling approach that captures both qualitative and quantitative dynamics.

The proposed system dynamics framework provides a powerful lens for practitioners to address the complexities of AI integration, moving beyond linear thinking to understand the interconnected factors driving or hindering adoption. By visualising these dynamics, audit firms can develop more resilient and adaptive strategies for AI implementation.

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