Exploring Factors Influencing the Adoption of AI Tools in Auditing: A Mixed-Methods Study

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Exploring Factors Influencing the Adoption of AI Tools in Auditing: A Mixed-Methods Study

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business at Virginia Commonwealth University

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First and foremost, I want to thank Allah for guiding me on this path and giving me the strength to continue. Without His divine guidance and blessings, I would not have had the resilience and perseverance to overcome the challenges and obstacles I faced throughout this journey.

Second, I want to express my gratitude to my parents for their unwavering love and support. To my mother, thank you for your long nights praying for me and encouraging messages. To my father, thank you for believing in me when I lacked belief in myself and for the unconditional love you have shown me. I am happy I made you proud. I love you both. To my in-laws, thank you for your love, support, and visits that made us feel at home and eased our long journey.

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With love,
Fahad
Abstract

Artificial Intelligence's (AI) rise has created value for organizations and society, prompting scholars to study its spread across many areas. However, the impact of AI adoption on governmental organizations still needs to be explored. Governmental entities face unique challenges distinct from private organizations, and existing research often focuses on the perspectives of AI experts or senior management, neglecting the insights of lower-level employees who will use the system daily.

This study investigates the multifaceted factors influencing the intention to adopt AI tools within a governmental auditing bureau in Saudi Arabia. To the best of our knowledge, no previous study has specifically delved into AI adoption within the context of governmental auditing in the literature. This study employs an exploratory mixed-method approach based on IS guidelines by Venkatesh et al. (2013, 2016). This research combines qualitative and quantitative methods to comprehensively investigate the factors influencing the intention to adopt AI tools in auditing.

Initially, the study identifies key factors and develops a conceptual model grounded in qualitative data and theoretical background. The model is then validated and tested through a survey using a larger sample within the governmental bureau. The findings support many hypotheses, emphasizing the significance of technological factors such as AI complexity, perceived scalability, relative advantage, and security in the intention to adopt AI tools in auditing. The study also highlights the need to align governmental auditing tasks and AI tools, and the importance of Task Technology fit. Organizational factors, such as leadership support and strategic AI implementation, are crucial for successfully adopting AI. Additionally, environmental factors underscore the pivotal role of higher authorities in facilitating and supporting AI adoption in governmental organizations.

This study offers several contributions. It extends the organizational AI adoption literature by broadening the understanding of AI adoption factors, emphasizing the value of studying government organizations due to their unique nature, and providing insights into the factors affecting AI adoption from the end-user's viewpoint. It offers practical benefits for the governmental auditing agency and similar governmental organizations. Educationally, this dissertation functions as a rich case study within the Information Systems (IS) field, providing a valuable educational resource.

Possible limitations include sample selection constraints, sample size in Phase I, and the limited contextual scope of the study. Directions for future research include examining the dynamics of AI implementation over time through longitudinal studies, testing the conceptual model across different governmental sectors and similar cultural and socio-political contexts, and investigating how AI tools affect auditors' compensation and job satisfaction.
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Abbreviations

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<tr>
<td>AA</td>
<td>AI Awareness</td>
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<td>AI</td>
<td>Artificial Intelligence</td>
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<td>AS</td>
<td>Auditees Support</td>
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<td>AVE</td>
<td>Average Variance Extracted</td>
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<td>CMB</td>
<td>Common Method Bias</td>
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<td>CR</td>
<td>Composite Reliability</td>
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<td>CX</td>
<td>AI Complexity</td>
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<td>HS</td>
<td>Higher Authority Support</td>
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<td>HTMT</td>
<td>Heterotrait-Monotrait Ratio</td>
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<td>IA</td>
<td>Intention to Adopt</td>
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<td>Leadership Support</td>
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<td>Partial Least Squares</td>
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<td>TOE</td>
<td>Technology-Organization-Environment Framework</td>
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CHAPTER 1: Introduction

In this chapter, we begin by examining the dissertation's research background. We then delve into the gaps in the literature and elucidate our rationale for conducting this study. Following that, we outline the dissertation's objectives and research questions. Subsequently, we explore the dissertation's contributions. Finally, we provide an overview of how the dissertation is organized.

1.1 Research Background and Context

1.1.1 Challenges in Organizational AI Adoption

The ascendancy of artificial intelligence (AI) has generated substantial value for both organizations and global society, with particularly striking examples of success evident in its contributions during the COVID-19 pandemic with Drug Discovery (Sharma et al., 2022). This notable impact has prompted the academic community to examine the proliferation of AI across various domains, including Healthcare (Alhashmi et al., 2019; Amisha et al., 2019; Powles & Hodson, 2017), Supply Chain Management (Riahi et al., 2021), Banking (Rahman et al., 2021), Hospitality (Chen et al., 2023; Nam et al., 2021), Human Resource Management (Agarwal, 2022; Pan et al., 2022; Pillai & Sivathanu, 2020), Insurance (Gupta et al., 2022), and many others. Projections indicate that AI's economic value is poised to make a remarkable $15.7 trillion addition to the global GDP (PwC, 2022) (Figure 1). Consequently, many organizations either adopt AI technologies or are eager to revamp their products, services, operational procedures, and even their entire business models (Gartner, 2019).
Figure 1. Contribution of AI to GDP by Region (PwC, 2022)

However, it is essential to acknowledge that organizations frequently encounter challenges in adopting AI to yield productive outcomes (S. Kar et al., 2021; van Giffen & Ludwig, 2023). One contributing factor to these setbacks lies in the accessibility and usability of AI technologies within organizations, as facilitating a user-friendly environment for members is pivotal in enabling them to harness and exploit AI to its full potential (van Giffen & Ludwig, 2023). Nevertheless, adopting AI promises to augment or even replace human decision-making and actions, unlocking the potential for human resources to be redirected toward more intellectually engaging and less repetitive tasks. Simultaneously, it offers the allure of heightened efficiency, reduced errors, and cost savings (Mikalef et al., 2019). Further, for AI adoption to flourish within organizations, it necessitates a state of organizational readiness and access to specific human resources and expertise, as underscored in the research (Weber et al., 2022). Shortcomings in the domains of clear leadership, strategic direction, and deployment guidelines, inclusive of standardized data collection and sharing procedures, have been recognized as impediments to the smooth assimilation of AI (S. Kar et al., 2021; Van Noordt & Misuraca,
Furthermore, governmental regulations, exemplified by the General Data Protection Regulation (GDPR), tend to introduce complexities into AI adoption across various industries.

Given these multifaceted challenges, it becomes imperative to comprehend both the driving forces that promote AI adoption and the barriers that hinder it. Consequently, further research is necessary to provide informed guidance for the successful adoption of AI in the public sector. Insights and lessons from previous research (S. Kar et al., 2021; Taeihagh, 2021; Van Noordt & Misuraca, 2022; J. Wong et al., 2022) serve as a valuable foundation for us to comprehend the challenges in AI adoption. However, it's crucial to acknowledge that adopting AI within governmental settings is multifaceted, entailing meticulous consideration of factors such as regulatory and governance mechanisms, technical constraints, societal and ethical implications, and participatory governance principles. Next, we discuss the potential of AI in government organizations.

1.1.2 AI Potential for Government Organizations

AI has gained significant attention recently due to its potential to transform various sectors, including government organizations. Adopting AI in government organizations can improve efficiency, enhance decision-making, and improve service delivery. However, the adoption of AI in government organizations faces additional challenges. This section explores the current state of AI in government organizations, including the challenges, opportunities, and factors that could influence their decision to use AI.

Government organizations encounter numerous challenges in the adoption of AI. One of the key challenges is the readiness of organizations to use AI technologies. Organizational readiness encompasses both technical readiness and the skillset of human resources (Kurup &
Gupta, 2022). Government organizations must have the necessary infrastructure, data management systems, and technical expertise to implement AI effectively. Additionally, the availability of high-quality data is essential for successfully implementing AI technologies (Wu et al., 2020). However, data quality and availability can be challenging in government organizations, as data may be fragmented, incomplete, or of poor quality, as seen in Healthcare Information Systems (Dixon et al., 2013).

Another potential challenge is the ethical and regulatory aspects of AI use in government organizations. Using AI in decision-making processes raises concerns about transparency, fairness, and accountability (Prunkl et al., 2021). There is a need for clear guidelines and regulations to ensure that AI systems are used ethically and responsibly in government organizations. Additionally, the potential impact of AI on employment and job displacement is a concern that needs to be addressed (Nguyen & Malik, 2021). Government organizations must consider AI adoption's social and economic implications and develop strategies to mitigate negative consequences.

Despite the challenges, AI in government organizations offers several opportunities for improved service delivery and decision-making. One of the key opportunities is the ability to analyze large volumes of data to derive insights and make informed decisions (Alsheibani, Messom, & Cheung, 2020a). AI can assist in data mining and analysis, enabling government organizations to extract valuable information from vast amounts of data. This can lead to more effective policymaking, resource allocation, and service provision. Furthermore, AI can enhance the efficiency of government processes by automating repetitive tasks and streamlining workflows (Noordt & Misuraca, 2020). By automating routine administrative tasks, government organizations can free up resources and allocate them to more complex and value-added
activities (Noordt & Misuraca, 2020). This can result in cost savings and improved productivity. In essence, the strategic integration of AI technologies presents a transformative potential for government entities, fostering operational efficiency and substantial advancements in service quality and decision-making capabilities.

Regarding factors influencing the decision to adopt AI, leadership support emerges as a critical determinant, a lesson gleaned from successful implementations in the private sector (Kurup & Gupta, 2022). Leaders in government organizations need to champion the use of AI and provide the necessary resources and support for its implementation. Additionally, the availability of technical resources and expertise is essential. Government organizations must invest in training and upskilling their workforce to ensure they have the necessary skills to implement and utilize AI technologies effectively. Organizational culture also played a significant role in adopting AI (Kurup & Gupta, 2022). A culture that embraces innovation, experimentation, and risk-taking is likelier to adopt AI technologies. Government organizations must foster a culture encouraging collaboration, learning, and openness to new technologies.

In summary, using AI in government organizations offers significant opportunities for improved service delivery, decision-making, and efficiency. Government organizations must identify areas where AI can bring value and demonstrate its potential benefits. Use cases such as predictive analytics for fraud detection, natural language processing for citizen services, and machine learning for policy analysis can showcase the value of AI in government organizations. However, some challenges must be addressed, including organizational readiness, ethical considerations, and regulatory frameworks. Factors such as leadership support, technical resources, organizational culture, and the availability of use cases influence the adoption of AI in government organizations. By addressing these challenges and leveraging these factors,
government organizations can harness the potential of AI to enhance their operations and provide better services.

1.1.3 AI in Auditing

According to the World Economic Forum's 2015 report, by 2025, approximately 75 percent of corporate audits could be completed with the assistance of AI, potentially automating up to 30 percent of these audits. According to a recent study conducted by PricewaterhouseCoopers (PwC, 2022), a prominent member of the big four accounting firms, it is projected that by the year 2030, AI is expected to contribute significantly to the global economy with a substantial increase of 14%, equivalent to a value of approximately US$ 15.7 trillion.

This shift towards automation promises to free auditors from repetitive tasks, granting them more time for in-depth analysis. As a result, auditors can focus on addressing the most critical risk areas, thereby gaining a clearer perspective on the larger context, and unlocking substantial economic potential. In Auditing, recent work has concentrated on examining AI adoption to explore the influential factors affecting its adoption within the organizational landscapes of both the United States and Australian contexts (Alsheibani, Messom, & Messom, 2020; Rawashdeh et al., 2022; Seethamraju & Hecimovic, 2022).

AI is a transformative force in the field of auditing, signifying the application of computer systems and adaptive algorithmic processes that emulate human-like intelligence. This AI adoption is directed toward optimizing and automating decision-making, cognitive functions, and the intricate interpretation of auditing data. It functions as a versatile and flexible tool,
described as a "hybrid set of technologies that complements and reshapes the audit process" (Issa et al., 2016) in the auditing context.

To exemplify AI's practicality in auditing, one can observe its profound influence on analyzing intricate auditing data, particularly contracts. Through machine learning software, auditors can efficiently assess a significantly larger volume of contracts, including complex leases, in a fraction of the time traditionally required for manual analysis (EY Reporting, 2018). Empirical evidence from a pilot study conducted by (EY Reporting, 2018) supports the advantages of AI tools in auditing by demonstrating their superior accuracy in identifying vital information within lease contracts compared to human reviewers.

AI's applications within auditing extend to identifying significant inaccuracies within the general ledger and streamlining expense audits (Kantarci, 2021). These diverse applications underline AI's transformative potential in auditing, promising to enhance efficiency and augment decision support for professionals in the field. In real-world scenarios, the impact of AI on auditing is substantial. Integrating AI technologies can elevate audit quality, enhance efficiency, and improve fraud detection effectiveness (Fedyk et al., 2022). Furthermore, the adoption of AI in auditing streamlines repetitive, structured tasks, allowing auditors to focus on more intricate and value-added activities (Fedyk et al., 2022).

In the realm of auditing, several AI tools and applications exist. Deloitte, for instance, employs Argus, a machine learning tool capable of comprehending leases, derivatives contracts, and sales contracts (Davenport, 2016). Argus has algorithms to identify critical contract terms, trends, and anomalies (Dickey et al., 2019). Another notable example is Halo, a machine-learning technology currently utilized by PricewaterhouseCoopers (Kokina & Davenport, 2017).
Halo scrutinizes journal entries and can flag potentially problematic areas, including entries with suspicious keywords, entries from unauthorized sources, or an unusually high frequency of journal entry postings outside authorized limits (Dickey et al., 2019). While the Big Four accounting firms increasingly embrace audit platforms and predictive analytics, they have yet to fully harness higher intelligence and cognitive capabilities (Kokina & Davenport, 2017). Nevertheless, these instances permit auditors to assess every journal entry a company or organization makes annually by scrutinizing all journal entries and focusing solely on the high-risk outliers; the auditing processes' speed and quality witness significant enhancements.

Integrating AI in organizational auditing introduces several significant drawbacks that need careful consideration. One primary concern is the inherent risk of bias in AI systems. AI algorithms, especially those based on machine learning, are trained on historical data (Landers & Behrend, 2023). If this data is biased or unrepresentative, the AI system can learn and perpetuate these biases, leading to skewed auditing outcomes. For example, if past data contains biases against certain demographic groups, the AI may disproportionately flag transactions involving those groups as high-risk, even if they are not. This can lead to unfair treatment and perpetuate systemic biases within the organization. Such biases can undermine the credibility of the auditing process and harm the organization’s reputation.

Additionally, the transparency and explainability of AI systems in auditing present significant challenges. Many AI algorithms operate as "black boxes," where their decision-making processes are not easily interpretable by humans. This opacity can be problematic in auditing, where understanding the rationale behind decisions is crucial for ensuring accountability and trust. When auditors cannot fully understand or explain how an AI system arrived at a particular conclusion, it can be difficult to justify decisions to stakeholders or
identify and rectify errors in the system. This lack of transparency can erode confidence in the audit process and create challenges in regulatory compliance. Furthermore, over-reliance on AI may reduce the role of human auditors, whose professional judgment and contextual understanding are vital for interpreting complex financial data and making nuanced decisions (Fedyk et al., 2022).

Moreover, Auditors may be apprehensive about potential job displacement or job loss. However, experts in the field of accounting argue that the demand for human accountants will remain, although their required skills may evolve (Agnew, 2016; Kokina & Davenport, 2017). As described in a paper by Huang et al. (2019), workers should emphasize interpersonal skills and delegate analytical and cognitive tasks to AI. AI will assist auditors in optimizing their time, enabling them to apply human judgment to analyze a broader and more profound spectrum of audit data and documents, ultimately enhancing their overall effectiveness.

AI's impact on auditing is multifaceted, encompassing technical advancements, ethical considerations, and audit quality and efficiency improvements. AI's significance in the real world lies in its potential to enhance auditing practices, improve decision-making processes, and contribute to the overall effectiveness and integrity of the audit profession.

1.1.4 Saudi Arabia and the Transformative Efforts

Saudi Arabia is amid a significant digital transformation endeavor driven by its ambitious Saudi Vision 2030 agenda (EY, 2022). This visionary roadmap is underpinned by three core pillars: creating a vibrant society, establishing a thriving economy, and cultivating an ambitious nation. These pillars harness the nation's inherent strengths to empower Saudi citizens to pursue their dreams. As part of the comprehensive initiatives to realize Vision 2030's objectives, Saudi
Arabia has launched its National Artificial Intelligence Strategy as part of its Digital Government Strategy (Radwan, 2023). This strategic move encompasses diverse areas of implementation critical to the program’s success and includes the ambitious goal of training more than 2,000 Saudi data and AI specialists. Notably, on a global scale, various sectors within the healthcare industry, such as pharmaceuticals, disease monitoring, and nursing, are already harnessing AI to enhance and optimize their services (Alhawassi et al., 2018; Kosárová, 2020). Moreover, Saudi Arabia has been at the forefront of AI adoption, as exemplified by the Saudi Data and Artificial Intelligence Authority (SDAIA) employing AI for the development of applications, chatbots, and data integration during the COVID-19 lockdown (Hassounah et al., 2020). This Vision 2030 framework, driven by a commitment to reduce the nation’s reliance on oil, seeks to diversify the economy and foster the growth of public service sectors, including health, education, infrastructure, recreation, and tourism.

Figure 2. AI contribution in the Middle East by USD (PwC, 2023)
Figure 3. The average annual growth in the contribution of AI by region between 2018-2030 (PwC, 2023)

PricewaterhouseCoopers (PwC) has unveiled staggering figures that underline the substantial impact AI is poised to make in the Middle East, with a projected economic contribution of approximately $320 billion (PwC, 2023). Among the nations in the region, Saudi Arabia stands to reap the most substantial rewards, with an estimated windfall of around $135.2 billion by 2030, constituting a remarkable 43% share of the entire Middle East (Figure 1). Moreover, PwC anticipates robust annual growth in AI’s contribution, ranging from 20% to 34% across the region annually (Figure 2). Strategic investment in AI technologies, aimed at advancing non-oil sectors, has the potential to firmly establish the region’s competitive position for the foreseeable future. This forward-looking approach ensures the region’s sustained growth and resilience in the years ahead, fostering diversified economic strength beyond oil-dependent industries.
This expansive growth is poised to profoundly reshape Middle Eastern markets, giving rise to innovative services and novel business models (Figure 4). AI's transformative potential in the Middle East is unequivocally significant, with vast implications for various sectors and industries.

1.2 Research Gap and Rationale

The existing body of literature on AI adoption in organizations exhibits several noteworthy gaps and unexplored areas that warrant further investigation. In the existing research on AI adoption in organizations, most studies have mainly looked at how AI is used in private and public organizations (Gupta et al., 2022; Horani et al., 2023; Phuoc, 2022; Pillai et al., 2022; C. Sharma et al., 2023), while there's been less focus on how it's used in government agencies. Government agencies differ from public organizations since they are funded explicitly by taxpayers and operate under government authority. In contrast, in a broader category, public organizations include government and non-government entities serving the public but with varied funding sources and structures. Government organizations face challenges different from those faced by private businesses. Recent studies have underscored the significance of
investigating the impact of AI on government organizations due to the limited research conducted in this domain (Alshahrani et al., 2022; Sun & Medaglia, 2019). Governmental organizations grapple with dynamic and ever-evolving environments, and their unique solution requirements demand a tailored approach, unlike the one-size-fits-all strategies frequently employed in private organizations.

Second, another notable gap pertains to the composition of the study samples. Existing research on AI adoption in organizations has predominantly centered on AI experts and senior-level management, shaping the discourse surrounding AI adoption from their vantage point (Demlehner & Laumer, 2020; Horani et al., 2023; Hradecky et al., 2022; Merhi, 2023). While the perspectives of experts and top-tier management are undoubtedly valuable, it is essential to recognize that most end-users comprise lower-level employees who interact with AI-enabled systems daily (Chiu et al., 2021; Tambe et al., 2019). Gaining insight into their perspectives is crucial for comprehending the genuine factors that influence the organization-wide adoption of AI tools.

Finally, in terms of methodological approaches, the current landscape primarily consists of qualitative studies (Alsheibani, Messom, & Messom, 2020; Hradecky et al., 2022; Nam et al., 2021; Schlegel et al., 2023; Seethamraju & Hecimovic, 2022), which identify factors without subjecting them to rigorous testing, and quantitative studies that often transplant factors from previous contexts (Agarwal, 2022; Chen et al., 2023; Kurup & Gupta, 2022; Pan et al., 2022; Rawashdeh et al., 2023), which may not always align with the specific case under examination, particularly in the case of governmental entities. Even among studies employing a combination of these methods (Rahman et al., 2021; Vasiljeva et al., 2021), there is a tendency to compare disparate sample groups that lack meaningful connections, such as contrasting the perspectives
of employees and consumers in the context of banking (Rahman et al., 2021). Consequently, adopting a mixed-method approach, incorporating both quantitative and qualitative elements, can wield a more robust impact in unraveling the complex nature of government organizations. Furthermore, to our knowledge, no previous study has delved explicitly into AI adoption within the context of governmental auditing. Also, different cultural backgrounds can affect the adoption of such technology in regions like the Middle East. Thus, context is the key differentiator for this study. Such context in research is classified based on different factors: geographical, organizational, cultural, and human characteristics (Davison & Martinsons, 2016). Research has found disparities between Western and Eastern cultures in their perceptions and behaviors towards innovations and their decision-making (Ali, 1993; Chen & Zahedi, 2016). Thus, researchers must clearly and adequately present the context settings of their research as the research is designed and theories are formulated as context plays a key role in theoretical contribution (Davison & Martinsons, 2016; Whetten, 1989).

In conclusion, the existing literature on AI adoption in organizations underscores several key areas for further exploration. It is essential to extend the research focus to encompass government organizations and recognize their distinct challenges in dynamic environments. Moreover, considering the perspectives of lower-level employees, who are primary users of AI systems, is crucial for a comprehensive understanding of AI adoption factors. Finally, using a mixed-method approach can provide a more nuanced comprehension of AI adoption, especially within the context of government entities, offering the potential for unique case studies beneficial for educational purposes. Addressing these gaps promises to advance our understanding of AI adoption in organizational settings.
1.3 Research Objective and Questions

This study employs an explorative mixed-method approach, combining interviews and surveys, to comprehensively investigate the multifaceted factors influencing the adoption of AI tools within a governmental auditing bureau in Saudi Arabia. Our research builds upon existing knowledge and extends it, offering fresh insights into organizational AI adoption, particularly at the intersection of AI and auditing. The outcomes of this research carry significant implications for both governmental auditing entities and auditing firms, providing valuable insights into the facilitators of AI adoption within the auditing domain.

To bridge the gap in the literature, we employ a mixed-method approach, following the guidance of Venkatesh et al. (2013, 2016), which recommends including a question for each method used. These questions are as follows:

1. "What are the factors among employees that could influence a governmental agency's intention to adopt AI in its auditing workflow system?" This qualitative question delves into the factors affecting the intention to adopt AI, capturing insights from end-users who may use the system.

2. "What are the outcomes of these factors influencing the intention to adopt AI?" This quantitative question aims to test and validate the factors identified in the qualitative findings, providing an organization-wide perspective, primarily from the auditors' standpoint.
3. "Are the factors identified in the qualitative study, and as captured through our model, supported by the results of the quantitative study?" This final question enables us to analyze the combined results of the previous questions and discuss the findings in-depth, assessing the support for our conceptual model.

1.4 Research Contribution and Significance

Our research significantly contributes to various dimensions, including theoretical, practical, and educational aspects.

**Theoretical Contributions:**

- **Extending Organizational AI Adoption Literature:** Our research significantly expands the existing Organizational AI adoption literature by delving into the factors influencing AI tool adoption within governmental organizational settings, particularly in the context of auditing. Unlike previous research, which has predominantly centered on private and public sector organizations (Gupta et al., 2022; Horani et al., 2023; Phuoc, 2022; Pillai et al., 2022; C. Sharma et al., 2023), our study offers a fresh perspective that expands the current theoretical framework.

- **Uniqueness of Governmental Agency Type:** Our research capitalizes on the uniqueness of our governmental agency bureau case study, contributing further insights into the factors affecting the intention to adopt AI. This approach broadens the understanding of AI adoption factors and emphasizes the value of studying government organizations. Furthermore, these findings are relevant to similar agencies in other countries, such as the GCC countries, where contextual similarities to Saudi Arabia are evident.
• **Shifting Focus to End-Users**: Unlike prior research that often prioritizes expert perspectives (Demlehner & Laumer, 2020; Horani et al., 2023; Hradecky et al., 2022; Merhi, 2023), our study shifts the focus to end-users of AI tools. This approach extends the findings of the literature by providing insights into the factors affecting AI adoption from the user's viewpoint, contributing to a more comprehensive understanding.

**Practical Contributions:**

• **Benefits for the Governmental Auditing Agency**: The findings from our research offer practical advantages. First, the governmental auditing agency in our case study will benefit by understanding the factors influencing AI adoption from their employees' perspectives. This knowledge will facilitate a smoother transition toward AI adoption and promote successful implementation.

• **Relevance for Similar Governmental Organizations**: Governmental organizations with analogous setups can draw valuable lessons from our research findings. This includes other governmental agency bureaus in countries with regulatory bodies resembling our case study, such as countries in the GCC. Our research outcomes can assist these organizations in comprehending the factors that influence AI adoption, thereby aiding their decision-making processes.

• **Cultural Insights**: The study's exploration of cultural differences in AI adoption factors offers practical insights to senior-level managers and organizational leaders operating within multinational environments. Organizations with global operations will gain a nuanced understanding of AI adoption dynamics across different regions,
contributing to informed decision-making when planning AI adoption for products and services.

**Educational Contributions:**

- **Rich Case Study for IS Education:** Our research functions as a rich case study within the Information Systems (IS) field, providing a valuable educational resource. The complex interplay of factors in adopting AI tools, especially in the distinctive context of governmental auditing, serves as an exemplary teaching tool. This educational contribution aligns with Lee’s (2019) recommendation to incorporate real-world cases into IS education, offering students and researchers an opportunity for in-depth learning and comprehensive understanding.

In summary, our research extends the theoretical foundations of AI adoption, provides practical insights for governmental auditing agencies and similar organizations, and offers a robust educational resource for IS students and researchers. These contributions collectively advance the knowledge and understanding of AI adoption in organizational settings, particularly in the unique context of government organizations.

1.5 Dissertation Organization

The subsequent sections of this dissertation proposal are structured as follows: The second chapter encompasses a comprehensive literature review, highlighting relevant research and pinpointing gaps in prior studies. The third chapter outlines our mixed methods approach, providing an overview. The fourth chapter delves into Phase I of our mixed methods approach, employing a qualitative methodology. The fifth chapter presents our conceptual model deduced
CHAPTER 2: Literature Review

This chapter reviews relevant literature in four parts. The first part provides an overview of AI in Auditing (Section 2.1). The second part discusses the organizational adoption theories (Section 2.2). The final part discusses the literature on AI adoption in organizational settings (Section 2.3).

2.1 Artificial Intelligence in Auditing

2.1.1 Overview and Relevant Work

In auditing, AI can be characterized as a "hybrid set of technologies complementing and transforming the audit process" (Issa et al., 2016). AI has the potential to significantly enhance efficiency, reduce costs, and improve the overall quality of audits. While AI is increasingly utilized in auditing, it's essential to note that its application is still in its early stages, primarily focusing on routine audit tasks like internal control monitoring (Moffitt et al., 2018). These developments have implications for accounting education, particularly for future accounting students who must possess accounting knowledge and technical skills to thrive in this evolving landscape (Qasim & Kharbat, 2020). Finding the right balance between traditional accounting expertise and IT skills relevant to the accounting profession is crucial. Additionally, Kokina & Davenport (2017) underscore the importance of future research in understanding the extent to
which human auditors rely on AI-generated results and the potential benefits or challenges that arise as these systems become more advanced and sophisticated. Thus, it is imperative to delve into the human factors that influence the adoption of AI technology within the auditing profession.

Challenges in implementing AI in auditing arise from various factors, including ethical considerations, algorithmic complexities, and the nature of AI technologies. One of the main concerns is the potential impact on human workers, as there are fears that AI may jeopardize job opportunities (Jobin & Ienca, 2019). Additionally, there are concerns about the misuse of AI by malevolent actors and the potential for bias in AI systems, which can undermine fairness and accountability (Jobin & Ienca, 2019).

The nature of some AI technologies poses challenges for auditing practices. AI systems often use complex algorithms that may be difficult to understand and evaluate (Minkkinen, Laine, et al., 2022). This lack of transparency can make it challenging for auditors to assess the reliability and accuracy of AI systems. Furthermore, integrating AI in auditing requires addressing ethical considerations, such as balancing human-provided learning and machine-assisted learning (Luan et al., 2020).

Another area of concern is the interaction between auditors and AI systems. While the audit profession is optimistic about AI’s potential to enhance audit quality, limited research exists on how auditors will interact with AI systems and how AI may influence how auditors evaluate evidence (Commerford et al., 2021).

Furthermore, the challenges of implementing AI in auditing extend to the broader context of governance and accountability. Auditing AI systems requires considering the socioeconomic
impacts and externalities associated with their use (Costanza-Chock et al., 2022). The need for audits to address issues of transparency, fairness, and algorithmic bias is crucial for ensuring the ethical and responsible use of AI in auditing (Mökander et al., 2021). Additionally, integrating AI in auditing practices necessitates the development of standardized frameworks and guidelines to assess and govern AI systems effectively (Avinash & Harsh, 2023).

Numerous studies have explored the utilization of AI in auditing and its potential implications for the field. Debreceny & Gray (2011) emphasized the importance of corporate emails as a source of audit evidence, highlighting their potential to contain evidential information significant for auditors. They also provided an overview of data mining techniques applicable to email data, offering a means to enhance the auditing process. Syed (2014) delved into integrating AI into accounting systems, focusing on its application in auditing and tax-related tasks. They found that expert systems, a facet of AI, granted users substantial control over problem-solving and decision-making processes, reducing the need for supervision, and enabling more direct access to upper management. However, they noted that AI accounting technologies are underutilized in developing nations. This underutilization is primarily due to resource constraints, such as the lack of advanced technological infrastructure and financial limitations. Additionally, there is a scarcity of research and development focused on adapting AI technologies to these nations' specific needs and conditions. These challenges result in a slower adoption rate of AI in auditing within developing countries than their developed counterparts.

Several studies have explored decision-making theories in the context of auditing and assurance issues, with some theoretical applications but limited practical implementations. Afroze and Aulad (2020) investigated the perceptions of audit practitioners in Bangladesh, a developing country, regarding AI adoption in their work. They found that respondents needed
more knowledge of AI's use in auditing. They identified three variables influencing AI adoption in Bangladesh: auditors' skill transformation, computerization of audit work, and their knowledge of AI. Seethamraju & Hecimovic (2022) conducted a cross-sectional analysis of variables affecting AI adoption in Australian auditing firms. They identified issues, such as the challenges of documenting technology use for regulatory verification, perceived legal and reputational risks in financial auditing work, and conservative approaches by external regulatory bodies. Benbya et al. (2020) identified several key objectives for implementing AI in organizations, including enhancing process effectiveness, improving existing products and services, developing new offerings, enhancing decision-making, and reducing costs. Notably, reducing the workforce was found to be the least important objective for organizations.

Many studies have provided overviews of emerging technologies like AI in the literature on accounting information systems (AIS). Huerta & Jensen (2017) reviewed research papers discussing the role of big data in AIS, touching on themes such as improving analytical and data handling capabilities, addressing privacy and security concerns, exercising creativity, and assessing the impact of automation on the accounting profession. (Gray et al., 2014) explored expert systems research in the accounting literature over nearly four decades, focusing on AIS research and its evolution in the context of emerging technologies. They stressed the need for further research in this area as more organizations adopt advanced technologies in accounting.

In Business Intelligence (BI) and Data Analytics, Alles & Gray (2016) identified barriers to integrating big data into financial statement audits. They highlighted potential benefits, including the power of predictive analytics, the use of rich data sources for fraud detection, and the ability to identify warning signs and outliers. They also pointed out inhibitors, such as the need for direct access to client data, signals sent to clients regarding areas of concern, and
challenges associated with non-financial data and result interpretation. Krieger, Drews, and Velte (2021) investigated the adoption of advanced data analytics by audit firms, revealing that technological competence, both among auditors and innovation teams, significantly influences the successful adoption of technology throughout various phases of the adoption process. Rikhardsson and Yigitbasioglu (2018) analyzed the volume and content of material concerning the interplay between management accounting, business intelligence, and data analytics. Their findings underscored the limited research in the literature regarding the intersection of these three areas, sometimes collectively referred to as BI&A.

In addressing technical challenges, Lwakatare et al. (2020) identified 23 challenges associated with creating and maintaining large machine learning-based software systems in an industrial context. Notable challenges included adaptability, scalability, safety, and privacy. Benbya et al. (2020) raised concerns about unexplainable decision outcomes in AI systems, potentially leading to social dysfunctions. They highlighted blurred lines of responsibility, which can pose accountability issues, and privacy as a primary ethical consideration affecting AI adoption, primarily when the AI system generates decision outcomes that are challenging to explain due to complex feature layers.

In conclusion, implementing AI in auditing faces several challenges, including ethical considerations, algorithmic complexities, and the need for standardized frameworks and guidelines. Addressing these challenges is crucial for ensuring AI's responsible and effective use in auditing practices. Further research and development are needed to overcome these challenges and fully harness AI's potential benefits in auditing.
2.1.2 Focus on AI Tools in Auditing

AI tools in auditing have become increasingly important in recent years. AI auditing, also known as algorithmic auditing, has been proposed as a tool for operationalizing and assessing AI governance (Minkkinen, Niukkanen, et al., 2022). These tools address ethics, transparency, and accountability in AI systems (Ayling & Chapman, 2021). They provide evidence for auditors' evaluation and help auditors find errors and issues in financial reports faster (Dagunduro et al., 2023).

One area where AI tools are used is in the automation of audit processes. Robotic Process Automation (RPA) is a tool that focuses on artificial intelligence-based issues and aims to automate repetitive, structured, and labor-intensive tasks in auditing (Moffitt et al., 2018). This tool can improve efficiency and accuracy in financial auditing (Khan et al., 2021). Machine learning algorithms can also learn and summarize hidden rules from audit data, identify anomalies, and improve the audit process (Chen et al., 2022).

Another important aspect of AI auditing tools is their ability to assess the impact and fairness of AI systems. Tools such as Google's What-If Tool, IBM's AI Fairness 360, and Pymetrics' Audit-AI algorithm bias detection tool are designed to evaluate AI models for bias and explainability (Yarger et al., 2019). These tools help auditors ensure that AI systems are fair and unbiased in their decision-making processes.

Moreover, the leading four auditing firms, the Big4, are actively developing and deploying various AI tools (Seethamraju & Hecimovic, 2022). Their goal is to establish specialized niches and gain a competitive edge in delivering audit services (T. Sun & Vasarhelyi, 2018). For example, KPMG is testing 'Clara,' an intelligent audit platform that employs data
analytics and machine learning techniques to scrutinize information. It models this data against numerous assumptions to pinpoint potential risks auditors can consider when making judgments, such as assessing management's debt provisions. Nevertheless, we have yet to reach the stage of AI deep learning, where applications like 'Clara' can independently make judgments, including determining the audit opinion to be included in the reporting phase (Bakarich & O'Brien, 2021). PwC is developing 'GL.AI,' which is designed to identify irregularities within clients' general ledger accounts, and they are currently conducting trials for a comprehensive AI audit of cash accounts, as stated in PwC’s (2022) report. Likewise, Deloitte and EY harness natural language processing technology to analyze unstructured contractual data, a practice applied in both the planning and evidence audit stages (Deloitte Insights, 2019; EY, 2018).

Furthermore, AI auditing tools can also be used to assess the trustworthiness and transparency of AI systems. For example, surveys and assessments can be conducted to evaluate the transparency and trustworthiness of auditing AI tools, just like medical AI tools (Fehr et al., 2022). Additionally, ethics-based auditing frameworks have been developed to ensure the safe and ethically responsible use of AI systems (Mökander et al., 2021). These tools provide a systematic approach to auditing AI systems and ensuring they meet ethical standards.

In conclusion, the growing importance of AI tools in auditing, also known as algorithmic auditing, marks a pivotal advancement in AI governance. These tools are instrumental in addressing ethical, transparency, and accountability concerns within AI systems, offering tangible evidence for auditor evaluation and expedited error detection in financial reports. Their applications extend to automation, with RPA streamlining labor-intensive audit tasks and elevating efficiency and accuracy. Integrating machine learning algorithms further enhances the audit process by uncovering hidden patterns, identifying anomalies, and improving efficiency.
Significantly, AI auditing tools encompass the evaluation of AI system fairness and impact, utilizing specialized tools to detect and explain bias, fostering fairness and impartiality in AI decision-making. Developing ethics-based auditing frameworks also underscores the commitment to safe and ethically responsible AI system deployment. These tools collectively underpin a comprehensive and systematic approach to AI system auditing, emphasizing their invaluable role in shaping the future of AI governance and enhancing auditing practices.

2.2 Organizational Adoption Theories

2.2.1 Overview of Adoption Theories

Exploration of the processes by which organizations incorporate innovative technologies has yielded a rich tapestry of theories that seek to elucidate the intricacies of organizational technology adoption. Notably, these theories have drawn extensively from the well-established body of literature on the diffusion of innovations instead of focusing primarily on the micro-level examination of individual innovation adoption. Traditionally, individual technology adoption research has honed in on the behaviors and decisions of individual users. In contrast, diffusion research has taken a broader perspective, examining the adoption patterns of groups or collectives (Nagy, 2010). Given that organizations, at their core, are comprised of interconnected groups of individuals, the application of diffusion theories is a more apt and relevant framework for comprehending the complexities that arise within the organizational context (Fichman, 2000; Rogers, 1995).

During the past 20 years of IS research, quite a diverse body of theoretical and empirical work has accumulated on adopting and diffusing IT-based innovations (Jeyaraj et al., 2006). Further, prior IS research has used several theories as a theoretical lens or foundation in studying
the effect of technology adoption from both the individual and organizational levels (Kim et al., 2018). As a result, IS research has made significant progress in identifying factors that influence the adoption of new technology. Such theories used for identifying factors of adoption are Technology-Organization-Environment (TOE) (Tornatzky et al., 1990), the innovation of diffusion theory (DOI) (Rogers, 1995), institutional theory (IT), the technology acceptance model I (TAM) and II (UTAUT) (Davis, 1989; Venkatesh et al., 2003), Theory of Reasoned Action (TRA) (Tornatzky et al., 1990), Network Externality effects (Abrahamson & Rosenkopf, 1997), The Elaboration Likelihood Model (Petty & Cacioppo, 1981), and the rational expectation theory (Au & Kauffman, 2003), among others. In terms of adoption at the organizational level, we will focus on TOE, an established framework for adoption used in the IS adoption literature. These theories should be used in conjunction to understand the adoption process better. Furthermore, three variables, Innovation, Firm, and Environment, are linked to the risks and barriers of the adoption process (Molinillo & Japutra, 2017).

Among these many choices of IS technological adoption theories, we will be adopting the Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990), the innovation of diffusion theory (DOI) (Rogers, 1995), and Task-Technology Fit (TTF) as the theoretical basis of our mixed-method study that was identified inductively after the qualitative findings were analyzed. These theories have shown their applicability for adoption studies in the IS literature and have also been confirmed based on our qualitative findings, which makes these theories highly applicable to the qualitative goal of this study, which is to identify the factors related to the intent to adopt AI tools to handle the auditing tasks for auditors in a government organization. TOE, DOI, and TTF comprehensively address the three primary dimensions of our
research, encompassing organizational, environmental, and task-specific aspects and their relationships with AI adoption. This choice will be further explored in chapter 3.

2.2.2 TOE and DOI

Tornatzky et al. (1990) developed the TOE framework to determine the factors affecting an organization's adoption decision. The TOE framework asserts that technological, organizational, and environmental factors influence organizations and individuals' adoption and adaptation of technological innovations (Figure 5). The technological context refers to current and emerging technologies relevant to the organization. This examines how the features of the technologies available to an organization influence the adoption process. The organizational context refers to the characteristics and resources of the organization. This examines the linking structures between employees, organization size, and the number of slack resources. The environmental context includes the industry's structure, the presence or absence of technology service providers, competition, and the regulatory environment. The DOI theory was developed by (Rogers, 1995), and it is concerned with the progression of innovations or novel developments from creation to adoption. Focusing on the perceived characteristics of innovations, this covers five aspects: Relative Advantage, Compatibility, Complexity, Trialability, and Observability. Relative Advantage is the extent to which an invention is perceived as superior to the concept, program, or product it replaces. Compatibility is the degree to which the innovation aligns with future adopters' beliefs, experiences, and desires. Complexity is the difficulty of understanding and/or applying the invention. Trialability is the degree to which an invention can be evaluated or experimented with before deciding to implement it. Observability is the degree to which the breakthrough innovation produces observable effects.
2.2.3 TTF

Task-technology fit (TTF) is a concept widely studied in various domains. TTF theory is a framework that focuses on the alignment between tasks and technologies to achieve optimal performance and user satisfaction (Goodhue & Thompson, 1995). It refers to the degree to which technology assists individuals in performing their tasks effectively and efficiently (Figure 6). When there is a good fit between a task and an information system (IS), it positively impacts task performance. Users are more likely to accept and use a technology when it aligns with their tasks and improves performance. This means that the technology's technical capabilities should align with the requirements of the task at hand.
TTF is not considered a standalone theory of organizational adoption but rather a concept closely related to adoption theories such as the Technology-Organization-Environment (TOE) framework. Task-technology fit refers to how technology aligns with or supports the tasks and needs of individuals or organizations. It emphasizes the importance of matching the features and functionalities of technology with the requirements and goals of the tasks being performed. TTF is often considered a critical factor influencing the successful adoption and implementation of technology within organizations. It helps to determine a technology's perceived usefulness and ease of use and its ability to enhance productivity and efficiency. Organizations can evaluate the potential benefits and challenges associated with its adoption by assessing the fit between the technology and the specific tasks.

While task-technology fit is not an adoption theory, it is often integrated into adoption models and frameworks to explain how the alignment between technology and tasks influences the decision to adopt and the subsequent adoption outcomes. It is particularly relevant in understanding technology acceptance and usage behaviors within organizations.
2.3 Research on AI adoption at the organizational level

2.3.1 Overview

Artificial intelligence has become a prominent phenomenon in organizational settings, transforming how businesses operate and compete in today’s market. AI technology has shown significant benefits for organizations, including increased revenue, cost reduction, and improved efficiency. However, despite its potential advantages, many organizations still grapple with whether to embrace AI. To evaluate the adoption of AI at the organizational level, it is essential to understand the factors that influence this decision-making process. In this section, we look at papers from the IS literature that studied the adoption of AI in organizational settings.

Research within the field of Information Systems (IS) has extensively examined the adoption of Artificial Intelligence (AI) within organizational contexts, spanning various domains such as Auditing (Alsheibani, Messom, & Messom, 2020; Rawashdeh et al., 2022; Seethamraju & Hecimovic, 2022), Auto Manufacturing (Demlehner & Laumer, 2020; Pillai et al., 2022; Smit et al., 2022), Digital Manufacturing (Chatterjee et al., 2021), Banking (Rahman et al., 2021), Healthcare (Alhashmi et al., 2019), Hospitality (Chen et al., 2023; Nam et al., 2021), Human Resource Management (Agarwal, 2022; Pan et al., 2022; Pillai & Sivathanu, 2020), Insurance (Gupta et al., 2022), Information Technology (IT) (Schlegel et al., 2023; Stecher et al., 2020), the Service Sector (Hradecky et al., 2022), Social Media Platforms (Kar & Kushwaha, 2023), and Telecom (H. Chen, 2019). This comprehensive investigation underscores the rapid and widespread transformation as organizations increasingly incorporate AI-driven tools.

Within this body of research, scholars have placed significant emphasis on identifying the key determinants that either facilitate or impede the adoption of AI technologies, seeking to
understand the multifaceted factors at play and shedding light on the intricate dynamics that shape the successful integration of AI solutions into diverse industries. Simultaneously, these studies aim to provide actionable insights for organizations looking to harness AI's potential to enhance efficiency, innovation, and competitiveness. These determinants include personnel dynamics, technical infrastructure, organizational structure, and external environmental elements, collectively shaping the path organizations take when integrating AI into their operations (Yu et al., 2023). Furthermore, AI adoption yields consequences that impact individuals, organizations, and employment scenarios, emphasizing the importance of comprehending both antecedents and outcomes for organizations aiming to maximize AI's potential while navigating its transformative effects on various aspects of their operations and workforce (Yu et al., 2023). Next, we discuss the papers based on their methodological approach due to the large number of studies in the organizational AI adoption literature.

2.3.2 Qualitative Studies

Exploratory qualitative studies serve as an effective initial step for researchers, enabling them to attain experience-near, contextualized, holistic insights and immerse themselves deeply in understanding the adoption of innovations within organizations and sectors (Sarker et al., 2013). In the context of this literature review, the qualitative studies primarily concentrate on expert viewpoints and employ a cross-sectional approach to identify influential factors. Among these studies, a prevalent focus centers on utilizing the Technology-Organization-Environment (TOE) framework as a guiding theoretical framework for factor identification (Alsheibani, Messom, & Messom, 2020; Demlehner & Laumer, 2020; Hradecky et al., 2022; Nam et al., 2021; Pumplun et al., 2019; Seethamraju & Hecimovic, 2022). Specifically, in terms of technology, interviews consistently highlight the significance of relative advantage and
compatibility as factors that positively influence the adoption of AI tools across the studies (Alsheibani, Messom, & Messom, 2020; Nam et al., 2021; Pumplun et al., 2019; Seethamraju & Hecimovic, 2022). Relative advantage is pivotal in enhancing organizational efficiency, productivity, and competitiveness (Alsheibani, Messom, & Messom, 2020; Nam et al., 2021; Pumplun et al., 2019). Moreover, it becomes evident that compatibility stands as a crucial determinant for the successful implementation of AI, necessitating a seamless alignment between the intended application and technology, alongside necessary adaptations to work processes to meet technological requirements (Alsheibani, Messom, & Messom, 2020; Pumplun et al., 2019; Seethamraju & Hecimovic, 2022).

From an organizational standpoint, a prominent recurring theme is the crucial role of top management support and its positive influence on the successful implementation of AI (Alsheibani, Messom, & Messom, 2020; Demlehner & Laumer, 2020; Pumplun et al., 2019). The endorsement of top-level management can significantly streamline the process of AI implementation. However, those in leadership positions must possess a fundamental understanding of the technology and its potential applications and demonstrate a steadfast commitment to nurturing an innovation-centric culture within the organization (Pumplun et al., 2019). Such a culture is essential to harnessing the full potential of AI technologies and ensuring their seamless integration into the organization's strategic objectives.

From an environmental perspective, two key factors emerged prominently: competitive pressure and customer readiness (Demlehner & Laumer, 2020; Nam et al., 2021; Pumplun et al., 2019; Seethamraju & Hecimovic, 2022). Qualitative findings reveal a direct connection between increased competitive pressure and a stronger inclination toward AI adoption (Demlehner & Laumer, 2020; Nam et al., 2021; Pumplun et al., 2019). This heightened pressure compels
organizations to actively embrace AI technologies to gain a competitive advantage. Additionally, customer needs and readiness to embrace AI tools are pivotal in facilitating or impeding their adoption within organizations (Nam et al., 2021; Pumplun et al., 2019; Seethamraju & Hecimovic, 2022). Understanding the alignment between these client requirements and the organization's AI initiatives is crucial for effective implementation.

Other qualitative studies employed in-depth case studies to investigate the relevant factors, choosing not to confine themselves to a specific theoretical framework. Jöhnk et al. (2021) delved into the components that define an organization's readiness for AI adoption to guide this process. Their research pinpointed several critical factors, including strategic alignment, resource allocation, cultural readiness, knowledge base, and data availability, all deemed integral for successful AI integration within an organization. Schlegel et al. (2023) examined the determinants of AI project failures by extensively exploring AI experts' perspectives. Their findings indicate that these determinants can be categorized into five primary areas: unrealistic expectations, issues related to specific use cases, organizational constraints, insufficient key resources, and technological challenges. Conversely, Bedué & Fritzsche's (2022) study employs the extended valence framework to explore how trust moderates perceived benefits and risks in shaping intentions to use AI, particularly during the early stages of technology development before actual implementation. Their research underscores the significance of knowledge accessibility, transparency, explain-ability, certification processes, and self-imposed standards and guidelines identified as essential requirements for mitigating uncertainties, fostering trust in AI, and ultimately promoting greater adoption intentions.
2.3.3 Quantitative Studies

A significant proportion of the studies on AI adoption within organizational settings, as highlighted in our literature review, predominantly employ quantitative approaches through the use of surveys (Agarwal, 2022; Alhashmi et al., 2019; Alsheibani, Messom, & Cheung, 2020b; Chatterjee et al., 2021; H. Chen, 2019; Chen et al., 2023; Gupta et al., 2022; Horani et al., 2023; Kinkel et al., 2022; Kurup & Gupta, 2022; Laut et al., 2021; Pan et al., 2022; Phuoc, 2022; Pillai et al., 2022; Pillai & Sivathanu, 2020; Rawashdeh et al., 2022, 2023; C. Sharma et al., 2023; Smit et al., 2022; Stecher et al., 2020). This methodological choice validates factors previously identified in the literature by widely distributing surveys to collect data from a diverse and substantial sample size. The prevailing trend among most studies involves the utilization of the TOE framework as the foundational theoretical basis for their research models, with only two exceptions. Alhashmi et al. (2019) examined the essential determinants for AI adoption within the healthcare sector by evaluating the relationship between intention to use AI and its actual usage using ETAM. Their findings underscore the significance of managerial, organizational, operational, and IT infrastructure factors, revealing their positive impact on perceived ease of use (PEU) and perceived usefulness (PU). As a result, these factors should be considered vital determinants in shaping the successful implementation of AI within the healthcare domain. On the other hand, Stecher et al. (2020) explored the connection between adopting AI and Enterprise Architecture, utilizing the resource-based view as their theoretical framework. Their results indicate that Enterprise Architecture has a notable, positive influence on AI adoption through its impact on three key aspects: the collaboration between AI and business units, the alignment of AI with business units, and the strategic flexibility of the IS infrastructure.
Regarding studies that primarily employed the TOE framework as their theoretical foundation, an examination from the technological perspective, as well as a comparison with findings in the qualitative literature, consistently reveals that both relative advantage and compatibility stand out as the predominant technological factors influencing the adoption of AI within quantitative research as well. Numerous studies across various industries have consistently demonstrated that relative advantage exerts a positive influence on AI adoption (Alsheibani, Messom, & Cheung, 2020b; H. Chen, 2019; Gupta et al., 2022; Horani et al., 2023; Phuoc, 2022; Pillai & Sivathanu, 2020). Interestingly, a surprising finding emerged from one study, indicating that Relative Advantage did not influence an organization's decision to adopt an AI tool for employee requirements despite its potential benefits, mainly due to its perceived complexity (Pan et al., 2022). Compatibility has also emerged as a factor with a positive impact on AI adoption (Alsheibani, Messom, & Cheung, 2020b; H. Chen, 2019; Horani et al., 2023; Phuoc, 2022; Rawashdeh et al., 2022, 2023). Nevertheless, it is worth noting that one study within the context of digital manufacturing did not uncover a significant association between compatibility and the intention to adopt AI (Chatterjee et al., 2021). This outlier result, however, may be attributed to limitations stemming from the sample size in that study. AI Complexity is another significant factor that was identified as having a negative impact on AI adoption (Gupta et al., 2022; Horani et al., 2023; Kinkel et al., 2022; Pan et al., 2022; Phuoc, 2022; C. Sharma et al., 2023). This perception arises due to its association with heightened implementation challenges, increased resource demands, greater error potential, and the necessity for extensive learning and adaptation, collectively rendering it a less appealing proposition for AI adoption.

From an organizational perspective, an in-depth literature examination reveals several pivotal factors. First, Top Management Support, which consistently aligns with qualitative
findings, stands out as a critical element in any organization's AI adoption journey (H. Chen, 2019; Chen et al., 2023; Gupta et al., 2022; Horani et al., 2023; Jadhav, 2021; Phuoc, 2022; Pillai & Sivathanu, 2020; Rawashdeh et al., 2022; C. Sharma et al., 2023). Its significance is widely acknowledged across various industries, as top management provides strategic guidance to attain competitive advantages. Likewise, managerial competence plays a substantial role in the AI transition (H. Chen, 2019; Phuoc, 2022). Leaders with a profound understanding of AI's implementation and utility are essential in making informed decisions, cultivating a positive workplace culture, efficient goal attainment, and fostering creativity and innovation. Second, Organizational Readiness emerges as a comprehensive factor encompassing technical capabilities, resources, and infrastructure necessary for successful AI implementation. While some studies focus on organizational readiness as a whole (Agarwal, 2022; Chatterjee et al., 2021; Phuoc, 2022; Pillai et al., 2022; Pillai & Sivathanu, 2020), others examine these facets individually (Chatterjee et al., 2021; H. Chen, 2019; Gupta et al., 2022; Horani et al., 2023; Jadhav, 2021; Kinkel et al., 2022; Laut et al., 2021; Pan et al., 2022). Nonetheless, these studies have a consensus that these factors significantly and positively influence AI adoption. Organizational readiness is critical as it ensures that a company is adequately prepared and equipped to effectively adapt to changes and confront challenges, ultimately contributing to its long-term sustainability and success. However, it is noteworthy that a few studies have reported differing findings (Chatterjee et al., 2021; H. Chen, 2019; Gupta et al., 2022; Pillai et al., 2022). Lastly, several studies addressed organizational size, yet the findings remained inconclusive (Kinkel et al., 2022; Pan et al., 2022; Phuoc, 2022). Specifically, one study argued that larger organizations may not offer sufficient resources to facilitate AI adoption (Pan et al., 2022). From
an organizational perspective, the literature underscores that certain crucial elements contribute to AI adoption, although their impact may vary.

From an environmental perspective, quantitative studies support the notion that competitive pressures significantly influence AI adoption, aligning with qualitative research findings. However, the literature exhibits conflicting views on this matter, with some studies suggesting that competitive pressures motivate organizations to adopt AI for a competitive advantage (Chen et al., 2023; Gupta et al., 2022; Kinkel et al., 2022; Pillai et al., 2022; Pillai & Sivathanu, 2020; C. Sharma et al., 2023), while others argue that their impact is non-significant, and potentially overshadowed by other adoption drivers (H. Chen, 2019; Horani et al., 2023; Pan et al., 2022; Phuoc, 2022; Rawashdeh et al., 2022). What's particularly noteworthy is the distinct divergence apparent in studies investigating the adoption of the same AI tool, namely robotic process automation, where certain studies identify it as a significant factor while others do not (Rawashdeh et al., 2022; C. Sharma et al., 2023). Second, Market uncertainty, characterized by industry or market unpredictability, doesn't consistently emerge as a significant factor in organizational AI adoption, possibly due to limited awareness of AI's predictive capabilities for factors affecting performance (H. Chen, 2019; Horani et al., 2023). It is another factor that contains conflicting perspectives and is interlinked with competitive pressures. Interestingly, one study contradicts this, indicating a positive and significant relationship between market uncertainty and AI adoption (Phuoc, 2022). Third, Vendor support consistently garners consensus as a crucial factor in the successful implementation and maintenance of AI tools over the short and long term (H. Chen, 2019; Horani et al., 2023; Phuoc, 2022; Pillai et al., 2022; Pillai & Sivathanu, 2020; Rawashdeh et al., 2022). Finally, government-related factors, including government regulation (Gupta et al., 2022; Horani et al., 2023; Jadhav, 2021; Pan et al., 2022),
government involvement (H. Chen, 2019; Phuoc, 2022), and government support (H. Chen, 2019; Chen et al., 2023), play a pivotal role in incentivizing AI adoption, although exceptions exist, such as auto manufacturing organizations showing decreased interest in compliance with strict regulations due to audit challenges (Pillai et al., 2022). Nonetheless, government involvement remains influential in fostering AI adoption across organizations.

2.3.4 Other Methods

In the existing literature, various studies have employed quantitative and qualitative research methods together to explore different facets of AI adoption. For instance, Rahman et al. (2021) conducted a study focusing on the factors influencing AI adoption intention in the banking industry, examining the perspectives of both employees and customers. Through qualitative analysis, they underscored AI's pivotal role in enhancing security while highlighting challenges such as regulatory compliance, privacy concerns, and skill and infrastructure limitations from an employee standpoint. In their quantitative investigation, Rahman et al. (2021) emphasized the significance of attitudes, perceived usefulness, trust, and social norms in shaping customers' intentions to adopt AI in the banking sector, with ease of use and awareness having minimal impact. Similarly, Vasiljeva et al. (2021) investigated attitudes towards AI, comparing employees and the general public. Notably, they found substantial differences in AI attitudes between employees in organizations with AI implementation and those without immediate plans, emphasizing the influence of top management attitudes, competitive dynamics, and regulatory considerations on AI adoption. This aligns with the research on qualitative and quantitative studies previously discussed.
Furthermore, Merhi (2023) employed the Analytic Hierarchy Process method to identify critical success factors in AI system implementation, which included top management support, IT infrastructure, and vendor support, aligning with prior literature. Lastly, Kar and Kushwaha (2023) utilized social media data analysis to uncover conversational opinions on AI adoption facilitators and inhibitors among employees. Their findings unveiled a range of factors, including efficiency, innovation, business research, product novelty, manual intervention, adaptability, emotional aspects, support, personal development, experiential learning, fear of failure, and reluctance to upgrade.

2.3.5 Conclusion

Nevertheless, substantial gaps persist within the existing body of literature. A cursory examination of the earlier studies highlights a predominant focus on private organizations and corporations. Consequently, it is imperative to acknowledge that government organizations may present a distinct set of challenges in the realm of AI adoption that differ from those encountered by their private counterparts, and a lack of research still exists in these types of organizations (Alshahrani et al., 2022; T. Q. Sun & Medaglia, 2019).

Second, the prevailing methodological approaches frequently gravitate toward a singular emphasis on quantitative or qualitative methods when investigating the factors driving AI adoption. However, these methodological approaches often need a more nuanced context for a deeper understanding of organizations, particularly in the case of governmental entities. Consequently, adopting a mixed-method approach, incorporating both quantitative and qualitative elements, can wield a more robust impact in elucidating the multifaceted phenomena. Moreover, this approach provides an invaluable opportunity for creating unique case studies.
suitable for classroom settings, as suggested by recent research. Even among studies employing a combination of these methods, there is a tendency to compare disparate sample groups that lack meaningful connections, such as contrasting the perspectives of employees and consumers in banking (Rahman et al., 2021).

Lastly, a noteworthy observation is that most studies rely on AI experts or senior-level management for insights rather than engaging with the end-users who will be actively utilizing the AI systems. In studies of this nature, it is imperative to prioritize the perspectives of the employees who regularly interact with the AI systems to accomplish organizational objectives and tasks (Chiu et al., 2021; Tambe et al., 2019). Therefore, when investigating factors that influence AI adoption, it becomes crucial to direct our focus toward the end-users, as their experiences and insights play an integral role in the successful integration of AI within organizations.

This extensive exploration within the IS literature enriches our comprehension of the intricate interplay between AI and organizational settings, offering valuable guidance for scholars and practitioners navigating the evolving landscape of AI adoption.
CHAPTER 3: RESEARCH METHODOLOGY

In this chapter, we explore our mixed-method research approach in the field of Information Systems (IS). Section 3.1 explains the mixed-method guidelines of IS research and comprehensively explores the foundations and relevance of mixed-method studies in the IS domain, offering insights into the unique advantages this approach brings to IS research. Qualitative or quantitative methods alone were inadequate for addressing the research question of the factors affecting the intention to adopt AI from the perspective of a governmental organization in a developing nation. Thus, we used a mixed-methods research approach for a comprehensive examination.

Section 3.2 explains our general mixed-method research methodology based on the mixed-method IS guidelines presented by Venkatesh, Brown, and Sullivan (2016), outlining the procedures and techniques employed to address our research questions effectively. Specific data analysis for each method will be discussed more in-depth in Chapter 4 for the Qualitative Phase and Chapter 6 for the Quantitative Phase. Finally, Section 3.3 provides a detailed description of the organization being focused on that is central to our research, providing a contextual backdrop for our mixed-method investigation.

3.1 Mixed-method study in IS

In the dynamic landscape of the IS field, where contextual dynamics frequently shift and established theories often fall short of providing comprehensive insights, combining quantitative and qualitative research approaches, known as mixed methods, emerges as a potent investigative tool (Tashakkori & Teddlie, 1998). The IS domain's intricate nature necessitates an approach that
captures numerical metrics and delves into the underlying intricacies and subjective dimensions of phenomena. Recognizing these challenges, mixed-methods designs have garnered prominence as they bridge the gap between quantitative rigor and qualitative depth (Venkatesh et al., 2013). This methodological approach allows researchers to holistically comprehend the multifaceted intricacies of IS phenomena and contributes to a more nuanced understanding of the subject matter.

Mixed methods present a multilateral advantage that significantly enhances the research process. First, this approach can address both confirmatory and explanatory research inquiries. It facilitates the validation of existing theories while unraveling underlying dynamics contributing to the observed phenomena. Second, mixed methods provide a more robust inference generation process than singular research methods or perspectives. By amalgamating the precision of quantitative analysis with the context-rich insights from qualitative exploration, mixed methods yield findings with greater credibility and validity (Venkatesh et al., 2016). Third, this approach fosters the generation of divergent and complementary viewpoints. It enables researchers to examine a research problem from multiple angles, enhancing the richness of the collected data and the depth of interpretation.

IS research is notably distinguished by its methodological diversity, which imparts a remarkable strength to the discipline (Venkatesh et al., 2013). Researchers in the IS discipline have harnessed an extensive repertoire of distinct research methodologies, which can, in essence, be comprehensively classified into three overarching categories: quantitative, qualitative, and design science research (Lee & Hubona, 2009; Myers & Avison, 2002; Peffers et al., 2007).
Various strategies for mixed-method design within IS research have been proposed. The initial methods tended to adopt a typological framework. For instance, Creswell (2003) delineated two fundamental forms of mixed-method designs: concurrent and sequential. While a typological approach could indeed aid researchers in selecting an appropriate design for their investigation (Teddlie & Tashakkori, 2003), the spectrum of mixed-methods studies is far more diverse than any single typology could fully encapsulate (J. C. Greene & Caracelli, 1997; Guest, 2013; Maxwell & Loomis, 2003; Tashakkori & Teddlie, 2003). The coexistence of multiple paradigms (such as positivist, critical realist, and postpositivist), the array of qualitative and quantitative methodologies at one's disposal, the extensive range of objectives for mixed-methods research, and the variations in terms of temporal orientation have rendered the implementation of mixed-methods designs considerably more intricate than mere alignment with a typology framework (Maxwell & Loomis, 2003).

In alignment with (Maxwell & Loomis, 2003), Venkatesh et al., (2013) contend that a more flexible approach to the design of mixed-methods research was necessary to address the constraints of the typology approach. Thus, they created guidelines for conducting mixed-method research. In their guidelines, they focus on three crucial aspects of conducting mixed methods research: (1) the appropriateness of a mixed methods approach; (2) the development of meta-inferences (i.e., substantive theory) from mixed methods research; and (3) the assessment of the quality of meta-inferences (i.e., validation of mixed methods research). However, the guidelines do not explore additional attributes that can be leveraged to formulate effective strategies for executing mixed-methods research. This omission underscores the potential for further investigation into a broader array of properties that could influence and enhance the design and implementation of mixed-methods research methodologies.
<table>
<thead>
<tr>
<th>Property of mixed-methods research</th>
<th>Design question addressed by the property</th>
<th>Possible dimensions</th>
</tr>
</thead>
</table>
| **Research questions** | How will the researcher write the research questions? | • Rhetorical style—format: questions, aims, and/or hypotheses  
• Rhetorical style—level of integration  
• The relationship of questions to other questions: independent or dependent  
• The relationship of questions to the research process: predetermined or emergent |
| **Purposes of mixed-methods research** | Which of the following purposes does the research design serve? | • Complementarity  
• Completeness  
• Developmental  
• Expansion  
• Corroboration/confirmation  
• Compensation  
• Diversity |
| **Epistemological perspectives** | Does the study involve one paradigm or multiple paradigms? | • Single paradigm stance  
• Multiple paradigm stance |
| **Paradigmatic assumptions** | What paradigmatic perspective will guide the research design? | • Pragmatism  
• Critical realism  
• Dialectical  
• Other major paradigmatic perspectives (e.g., postpositivism) |
| **Primary design strategies** | Does the study develop or test a theory? | • Exploratory investigation  
• Confirmatory investigation |
| **Strands/phases of research** | Does the study involve one or multiple phases? | • Single phase (or single study) or monostrand design  
• Multiple phases (or research program) or multistrand design |
| **Mixing strategies** | Does the design involve using both qualitative and quantitative research across all components of a study? | • Fully mixed methods  
• Partially mixed methods |
| **Time orientation** | Do the quantitative and qualitative data collection occur sequentially or | • Sequential designs  
• Concurrent designs |
<table>
<thead>
<tr>
<th>Priority of methodological approach</th>
<th>Concurrently?</th>
<th>Does the qualitative or quantitative component have priority or are they equally important?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>• Equivalent status design&lt;br&gt;• Dominant-less dominant design (i.e., qualitative&lt;br&gt;• dominant or quantitative dominant)</td>
</tr>
<tr>
<td>Sampling design strategies</td>
<td></td>
<td>Which of the following sampling designs does the researcher use in the data-collection stage?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Basic mixed-methods sampling strategies&lt;br&gt;• Sequential mixed-methods sampling&lt;br&gt;• Concurrent mixed-methods sampling&lt;br&gt;• Multiple mixed-methods sampling strategies</td>
</tr>
<tr>
<td>Data-collection strategies</td>
<td></td>
<td>What are the best strategies to collect the quantitative and qualitative data?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Multiple modes of data collection (both quantitative and qualitative data collection techniques)</td>
</tr>
<tr>
<td>Data-analysis strategies</td>
<td></td>
<td>How does the researcher analyze the qualitative and quantitative data?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Concurrent mixed analysis&lt;br&gt;• Sequential qualitative-quantitative analysis&lt;br&gt;• Sequential quantitative-qualitative analysis</td>
</tr>
</tbody>
</table>

**Inference decisions**

<table>
<thead>
<tr>
<th>Types of reasoning</th>
<th>Will a particular theoretical perspective drive the design?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Inductive theoretical reasoning&lt;br&gt;• Deductive theoretical reasoning&lt;br&gt;• Inductive and deductive theoretical reasoning&lt;br&gt;• Abductive theoretical reasoning</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Inference quality</th>
<th>Which quality issues does the researcher address in the study?</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>• Design and explanatory quality&lt;br&gt;• Sample integration&lt;br&gt;• Inside-outside&lt;br&gt;• Weakness minimization&lt;br&gt;• Conversion&lt;br&gt;• Paradigmatic mixing&lt;br&gt;• Commensurability&lt;br&gt;• Multiple validities&lt;br&gt;• Political</td>
</tr>
</tbody>
</table>

These guidelines were subsequently expanded upon in the work of (Venkatesh et al., 2016), encompassing the identification and incorporation of variations within mixed-methods research that were missing in the original guidelines (Venkatesh & Sykes, 2013). The guidelines' extension was achieved by incorporating various attributes intrinsic to mixed-methods research. This extension involved connecting diverse properties and discerning the interplay between different design choices. Such an approach aids researchers in orchestrating a well-structured mixed-methods study, where the correlation between distinct properties guides the progression...
from one design decision to another, ultimately contributing to developing a comprehensive and high-quality research endeavor. They identified 14 crucial properties inherent in mixed-method designs (Table 1). They are grouped into three different categories:

1. **Foundations of design decisions** – These are the preliminary decisions that guide the research design.
   - Research questions.
   - Purposes of mixed-methods research.
   - Epistemological perspectives.
   - Paradigmatic assumptions

2. **Primary design strategies** – These are decisions related to the strands/phases of research and the process of designing research.
   - Design-investigation strategies.
   - Strands/phases of research.
   - Mixing strategies.
   - Time orientation.
   - Priority of methodological approach.
   - Sampling design strategies.
   - Data-collection strategies.
   - Data-analysis strategies.

3. **Inference decisions** – These are decisions related to the development of meta-inferences, data interpretation, and inference quality.
   - Types of reasoning.
   - Inference quality.
Table 2. Properties Mapping Guidelines adapted from (Venkatesh et al., 2013)

<table>
<thead>
<tr>
<th>Guidelines (Venkatesh et al. 2013)</th>
<th>Properties of mixed-methods research</th>
</tr>
</thead>
</table>
| 1) Decide on the appropriateness of a mixed-methods approach. | **Foundations of design decisions:**  
- Research questions  
- Purposes of mixed-methods research  
- Epistemological perspectives  
- Paradigmatic assumptions |
| 2) Develop strategies for mixed-methods research designs. | **Primary design strategies:**  
- Design investigation strategies  
- Strands/phases of research  
- Mixing strategies  
- Time orientation  
- Priority of methodological approach |
| 3) Develop strategies for collecting and analyzing mixed-methods data. |  
- Sampling design strategies  
- Data-collection strategies  
- Data-analysis strategies |
| 4) Draw meta-inferences from mixed-methods results. | **Inference decisions:**  
- Types of reasoning |
| 5) Assess the quality of meta-inferences. |  
- Inference quality |
| 6) Discuss potential threats and remedies. | |

In summary, the Venkatesh et al. (2016) study expands upon the guidelines provided by (Venkatesh et al., 2013) by identifying and incorporating 14 distinct variations of properties inherent to mixed-methods research (Table 2). These guidelines offer a fresh perspective that accommodates the multifaceted nature of mixed methods designs. Furthermore, this research presents an in-depth exploration of a specific type of mixed-methods study. It also delves into developing and validating meta-inferences, which pertains to validating mixed-methods research in our illustrative case. This contribution enhances the evolution of mixed-methods research by considering mixed methods as an integrated design model that draws from various properties of mixed-methods research. Ultimately, this study advances our comprehension of mixed-methods research by showcasing the diverse applications of mixed methods and demonstrating that such an approach may yield more robust inferences due to its integration of qualitative and quantitative elements. Thus, we follow these specific guidelines to inform our research study.
3.2 Our Research Methodology

Considering the relative scarcity of studies addressing AI adoption within governmental organizations and the unique context of governmental auditing agencies, adopting mixed methods becomes even more pertinent. Our research objectives center on uncovering and substantiating the influence of AI adoption within the specialized context of a governmental auditing agency. Given the intricate interplay of factors specific to this domain, the mixed-methods approach aligns seamlessly with our research goals. It facilitates quantifying the effects of AI adoption and empowers us to delve into the intricate human and organizational dynamics that shape technology implementation within this distinct context. Further, the qualitative or quantitative method alone was inadequate for addressing the research question of the factors affecting intention to adopt AI from the perspective of a governmental organization in a developing nation. Thus, our choice of mixed methods reflects our commitment to comprehensively exploring the complex landscape of AI adoption in governmental auditing agencies, thereby contributing valuable insights to academia and practice.

The Mixed method guidelines in IS proposed by Venkatesh, Brown, and Sullivan (2016) comprise six steps. The following section describes each step in detail. Further details are available in Appendices A and B. In Appendix A, we offer an elaborate account of the decisions underpinning our mixed-methods design, drawing upon the framework provided by Venkatesh et al. (2016). In Appendix B, we present an illustration of our adherence to established criteria for mixed-method designs, as articulated by Venkatesh et al. (2013). The Appendices provide a comprehensive table view of the mixed method design choices and quality criteria.
Step 1: Decide on the Appropriateness of Mixed Methods Research

In alignment with the IS mixed method guidelines for assessing the suitability of mixed-methods research in a study, researchers must navigate decisions related to four critical elements: 1) research questions, guiding the exploration of the study's objectives; 2) research purposes, outlining the intended outcomes and contributions; 3) the selection of theoretical perspectives/worldviews or paradigms, influencing the underlying framework for analysis; and 4) epistemological perspectives, shaping the understanding of knowledge acquisition. These foundational components of mixed methods research collectively shape the design decisions essential for establishing the boundary assumptions that guide the research project. As researchers delve into these considerations, they not only define the scope and direction of their inquiry but also lay the groundwork for a robust and comprehensive research methodology (Creswell, 2003; Venkatesh et al., 2016)

Research Questions

In our study, we have followed the mixed-method research guidelines proposed by Venkatesh et al. (2016). Our approach begins by formulating three research questions for each method: one for the qualitative, one for the quantitative, and one for the mixed-method phase. We wrote the qualitative and quantitative research questions separately first and a mixed-methods research question second.

The Qualitative research question was: "What are the factors among employees that could influence a governmental agency's intention to adopt AI in its auditing workflow system?" This qualitative research question delves into the factors affecting the intention to adopt AI, capturing insights from end-users who may potentially use the system. The Quantitative research
question was: "What are the outcomes of these factors influencing the intention to adopt AI?"

This quantitative question aims to test and validate the factors identified in the qualitative findings, providing an organization-wide perspective, primarily from the auditors’ standpoint. The Mixed Method research question was: "Are the factors identified in the qualitative study, and as captured through our model, supported by the results of the quantitative study?" This final question enables us to analyze the combined results of the previous questions and discuss the findings in-depth, assessing the support for our conceptual model.

The questions were formulated in a question format. Specifically, the quantitative research question drew from the findings of the qualitative research questions. Additionally, the mixed-methods research question hinged on the outcomes of the quantitative and qualitative research questions. The interconnections between the questions and the research process were pre-established. This ensured a cohesive and logical progression in the study.

Purpose of mixed-methods research

In terms of the purpose of our study, our study falls into the “developmental” category (Venkatesh et al., 2016). This developmental category aims "to ensure the questions from one strand emerge from the inference of a previous one or one strand is used to develop hypotheses the researcher will test in the next one" (Venkatesh et al., 2013, 2016). Specifically, the qualitative phase focuses on conducting interviews to pinpoint the factors influencing the intention to adopt an AI tool from the perspective of government auditing in a developing nation. This phase is instrumental in constructing a model and formulating hypotheses for subsequent testing. Conversely, the quantitative phase corroborates the factors identified in the previous qualitative phase by conducting a comprehensive organization-wide survey.
Epistemological Perspective and Paradigmatic Assumptions

From the standpoint of epistemology, one has the option to engage in mixed-methods research by employing either a single paradigm or multiple paradigms. A viewpoint involving multiple paradigms asserts that different paradigms can coexist harmoniously and be applied within a single research project (Teddlie & Tashakkori, 2003). Thus, the use of multiple paradigms is suitable for our case.

In our study, using multiple paradigms within our epistemological strand leads us to adopt a dialectical stance (J. Greene & Hall, 2010; Tashakkori & Teddlie, 2003; Venkatesh et al., 2016). The dialectic paradigm perspective typically permits the incorporation of multiple paradigmatic traditions within a given research project or program. This assumes that employing various paradigms enhances the comprehension of the studied phenomenon (J. Greene & Hall, 2010; Tashakkori & Teddlie, 2003; Venkatesh et al., 2016). In our research, the qualitative segment predominantly employs an interpretive and grounded-theory perspective, while the quantitative phase shifts towards a positivist standpoint, involving the deductive testing of the model developed in the earlier phase.

Step 2: Develop Strategies for Mixed Methods Research Designs

Following the IS guidelines, once the appropriateness of mixed-methods research is established, the subsequent phase entails crucial design decisions concerning strands/phases of research, the prioritization of methodological approaches, design-investigation strategies, mixing strategies, and time orientation (Venkatesh et al., 2016). It is noteworthy that these interrelated decisions maintain the flexibility to operate independently and may undergo modifications as the study unfolds.
Strands/Phases of Research

In the framework provided by Teddlie & Tashakkori (2009), a strand or phase can be understood through three pivotal stages. The first stage is conceptualization, which engages with theoretical foundations, the study's purpose, and the chosen research methods. The second stage is the experiential phase, delving into the practical dimensions of data collection and analysis. Finally, the inferential stage encompasses subsequent phases focused on data interpretation and application. This delineation clarifies the multifaceted progression within a strand or phase as articulated by the authors. In mixed methods designs, two types are classified: monostrand designs and mixed methods multistrand designs (Teddlie & Tashakkori, 2003; Venkatesh et al., 2016).

Monostrand design integrates qualitative and quantitative elements within a single phase of the conceptualization-experiential-inferential process (Nastasi et al., 2010; Teddlie & Tashakkori, 2006; Venkatesh et al., 2016). In contrast, mixed-methods multistrand designs require at least two research strands, allowing the seamless blending of quantitative and qualitative components across all stages—conceptualization, experiential, and inferential processes (Teddlie & Tashakkori, 2006; Venkatesh et al., 2016). Notably, multistrand designs often extend beyond a singular phase, encompassing multiple phases within a comprehensive research program. Each phase diligently covers every stage, from conceptualization to inference, as outlined by (Teddlie & Tashakkori, 2009). Decisions regarding research strands/phases significantly impact choices in other design strategies, including methodological approach priority, mixing strategies, and time orientation. While monostrand designs have limitations (Teddlie & Tashakkori, 2006), mixed methods multistrand designs offer flexibility through
parallel, sequential, conversion, or multilevel mixed designs (Teddlie & Tashakkori, 2009; Venkatesh et al., 2016).

In essence, our study aligns with the IS Mixed Method guidelines, falling under the mixed-method "Multistrand" research design and embodying a "sequential exploratory design" in its methodology. This categorization indicates a structured approach involving multiple phases and a seamless blend between qualitative and quantitative aspects. The qualitative phase concentrated on identifying factors influencing the intention to adopt AI tools, while the subsequent quantitative phase was dedicated to testing these identified factors. This strategic alignment ensures a comprehensive exploration and validation of the research variables sequentially and systematically.

*Priority of Methodological Approach*

By considering the priority of the methodological approach, mixed-methods research designs in IS can be classified into two types: equivalent-status designs and dominant-less dominant status designs. For equivalent-status designs, “researchers generally conduct a study using both qualitative and quantitative approaches about equally to understand the phenomena of interest” (Tashakkori & Teddlie, 1998; Venkatesh et al., 2016). For dominant-less dominant status designs, “one paradigm and its methods are prevalent, while a smaller portion of the overall study is drawn from an alternative design” (Tashakkori & Teddlie, 1998; Venkatesh et al., 2016). Dominant-less dominant status designs can be further classified into two types: qualitative-dominant mixed-methods research and quantitative-dominant mixed-methods research (R. B. Johnson et al., 2007; Venkatesh et al., 2016). Qualitative-dominant mixed-methods research involves relying on a qualitative, constructivist-poststructuralist-critical
perspective in the research process. It acknowledges that incorporating quantitative data and approaches will likely enhance most research projects. In contrast, quantitative-dominant mixed-methods research relies on a quantitative, postpositivist view, recognizing that adding qualitative data and approaches will likely benefit most research projects.

Our study follows a "dominant less dominant design," with the quantitative study taking on the more prominent role (i.e., quantitative-dominant). In practice, this approach involves conducting the main study within a dominant paradigm, with a minor portion of the research incorporating elements from an alternative design (Tashakkori & Teddlie, 1998; Venkatesh et al., 2016). While it is crucial to establish the priority of the methodological approach, it is imperative to note that researchers maintain the flexibility to reconsider and modify this decision after the completion of the study (Teddlie & Tashakkori, 2009). This dynamic approach allows for adaptability and refinement based on the evolving needs and insights gained during the research process.

*Design Investigation Strategy*

The mixed-methods study aimed to construct and validate a research model encompassing the factors influencing the intention to adopt AI tools. The research aimed to conceptualize key determinants and rigorously test their impact, utilizing both qualitative and quantitative insights to achieve a nuanced understanding. This approach facilitated the exploration of intricate relationships and established a robust foundation for identifying the factors contributing to adoption intentions. Two mixed-method strategies have been identified in the IS literature: exploratory and confirmatory (Tashakkori & Teddlie, 1998). In the Qualitative Study, an Exploratory investigation strategy was employed to develop hypotheses and gain new
insights within our specific context. Conversely, the Quantitative study utilized a Confirmatory Investigation strategy to test existing theories using hypotheses established in the previous phase.

Mixing Strategies

The fundamental principle of mixed-methods research lies in the amalgamation or integration of methods and data. This approach is crucial as it enables researchers to extract insights from a variety of methods (Venkatesh et al., 2016). When designing a mixed-methods study, researchers must diligently consider decisions regarding the types of data to integrate, and the methodology chosen for their seamless integration. This thoughtful approach ensures a cohesive and comprehensive research design that maximizes the strengths of both qualitative and quantitative components.

Two dimensions of mixing strategies were proposed: fully mixed methods and partially mixed methods (Tashakkori & Teddlie, 1998; Teddlie & Tashakkori, 2009). A fully mixed-methods design entails the utilization of both qualitative and quantitative research throughout all aspects of a study, including objectives, types of data and operations, analysis methods, and inference types (Tashakkori & Teddlie, 1998). This design, often referred to as a mixed-model design, signifies the pinnacle of paradigm mixing, integrating qualitative and quantitative paradigms at various stages of the study. On the contrary, a partially mixed-methods design involves blending quantitative and qualitative elements at specific stages, such as sampling, data collection, data analysis, or data inference (Teddle & Tashakkori, 2009). This design offers flexibility for parallel mixing, sequential mixing across chronological phases, or mixing across multiple levels of analysis.
Our research aligns with the "Partially Mixed Method" mixing strategy, where the integration of qualitative and quantitative components occurs specifically during the data analysis and inferential stages. This deliberate blending of methods enhances the robustness of our study, fostering a comprehensive exploration of the research objectives. It allows for a nuanced understanding by leveraging both qualitative insights and quantitative rigor, ensuring a well-rounded approach to data analysis and interpretation.

*Time Orientation*

Mixed methods research can be categorized based on its time orientation into two main types: sequential and concurrent (Venkatesh et al., 2016). In sequential mixed methods designs, researchers typically engage in one strand of the study (e.g., qualitative) before advancing to the other strand (e.g., quantitative), with the sequencing guided by the study's objectives and research questions (Creswell, 2003). On the other hand, a concurrent mixed-methods design involves the simultaneous execution of the qualitative and quantitative components of the study (Castro et al., 2010; Teddlie & Tashakkori, 2006). This approach leverages both qualitative and quantitative data, employing independent analyses in separate strands to effectively address the research questions.

Creswell (2003) presents three variations of sequential mixed methods designs: 1) sequential explanatory, involving the quantitative phase preceding the qualitative phase; 2) sequential exploratory, marked by the qualitative phase preceding the quantitative phase; and 3) sequential transformative, which permits prioritizing either the quantitative or qualitative phase. This design incorporates a theoretical lens to guide the study's overall design, encompassing both components seamlessly.
The selection of time orientation in mixed-methods research is intricately connected to the research questions and objectives guiding the study. In our research, we adhere to the sequential exploratory mixed-method design, initiating with the qualitative phase and subsequently progressing to the quantitative phase. This sequential approach allows us to first explore and then validate theoretical constructs within a new context. This design choice aligns with the nature of our study, as suggested by Venkatesh et al. (2013).

Step 3: Develop Strategies for Collecting and Analyzing Mixed methods Data

Following the completion of crucial design decisions regarding strands/phases of research, design investigation strategies, priority of methodological approach, mixing strategies, and time orientation, the next critical step is the development of a comprehensive set of strategies for collecting and analyzing mixed-methods data (Venkatesh et al., 2016). Before initiating the data collection phase for their study, researchers are tasked with determining the strategy for participant selection and the appropriate number of participants, which involves incorporating sampling design strategies (Collins, 2010; Venkatesh et al., 2016).

Sampling Design Strategies

Sampling is a crucial aspect of the research process, impacting the quality of inferences and the generalizability of findings. In mixed-methods research, sampling decisions are vital for both qualitative and quantitative components. Teddlie & Yu (2007) present five mixed methods sampling strategies, while Onwuegbuzie and Collins (2007) offer a framework based on time orientation and the relationship between qualitative and quantitative samples. The convergence of these typologies results in four mixed-methods sampling designs: basic, sequential, concurrent, and multiple. Basic strategies encompass probability, stratified purposive, and
purposive random sampling associated with quantitative and qualitative studies. Sequential sampling involves using the first strand's methodology and results to inform the second strand. Onwuegbuzie and Collins categorize sequential designs into identical, parallel, nested, and multilevel samples based on their sampling strategies, each providing distinct insights into the mixed-methods approach to sampling (Collins, 2010).

Our sampling approach involved a sequential design with Parallel Sampling. In sequential sampling, the methods and findings of the initial phase inform the methodology of the subsequent phase (Teddlie & Yu, 2007). In the case of Parallel Samples, it means that the samples used in the quantitative and qualitative aspects of the research are distinct but drawn from the same underlying population (Tashakkori & Teddlie, 1998; Venkatesh et al., 2016). Therefore, while the samples in our study varied between the qualitative and quantitative components, they both originated from the same governmental organization. Notably, individuals from the qualitative sample were excluded from the quantitative sample. Due to the unique context of our case study within a governmental organization, the organization itself was responsible for selecting the sample for both the qualitative and quantitative phases, facilitated by their designated contact person.

*Data-collection Strategies*

The classification of data-collection strategies in mixed-methods research hinges on several key factors, including their predetermined nature, the utilization of closed- and open-ended questions, and their emphasis on numeric versus non-numeric data analysis (Creswell, 2003; Venkatesh et al., 2016). In essence, these strategies can be broadly categorized as quantitative, involving systematic and planned instruments or predetermined questions for data
collection, or qualitative, characterized by unstructured methods for data collection through observation or measurement (Tashakkori & Teddlie, 1998). This nuanced classification allows for a comprehensive understanding of the diverse approaches employed in mixed-methods research, providing clarity on the varying degrees of structure and focus on data-collection strategies. In mixed-methods research, recognizing the strengths and limitations of each data-collection strategy is crucial. Researchers can leverage one method’s strengths to compensate for another’s weaknesses within a single study (R. B. Johnson et al., 2007; Venkatesh et al., 2016).

In our study, we implemented a two-phase approach, commencing with qualitative data collection and followed by quantitative data collection. During the Qualitative phase, we utilized semi-structured open-ended questions guided by pre-designed interview guidelines. In contrast, the Quantitative phase involved closed-ended questioning, employing a traditional survey design for systematic data collection. This sequential design allowed us to gather in-depth insights through open-ended inquiries and subsequently obtain quantifiable data using structured survey methods.

Data-analysis Strategies

The analysis of data in mixed-methods research can be approached through three strategies: concurrent mixed analysis (simultaneous analysis of qualitative and quantitative data), sequential qualitative-quantitative data analysis (qualitative analysis followed by quantitative analysis), and sequential quantitative-qualitative data analysis (quantitative analysis followed by qualitative analysis) (Tashakkori & Teddlie, 1998). Various tools and methods, such as data reduction, data transformation, and data correlation, can be employed for analyzing mixed-methods data (R. B. Johnson et al., 2007; Venkatesh et al., 2016). Data conversion or transformation involves
converting qualitative data into numerical codes for statistical representation (quantized) or converting quantitative data into narrative for qualitative analysis (qualitized) (Teddle & Tashakkori, 2009). The choice between quantizing and qualitizing depends on the research goals and theoretical concepts guiding the study. While planning for data transformation can occur before or after data collection, it often happens unexpectedly during the analysis phase (Teddle & Tashakkori, 2009).

In our data analysis strategy, we adhered to a sequential qualitative-quantitative analysis design, strategically commencing with qualitative data analysis before transitioning to quantitative data analysis (Tashakkori & Teddle, 1998). We approached the qualitative data analysis not through "transformation" but by categorizing it into broad segments using the software ATLAS.ti. This sequential progression was chosen to construct a robust research model for the quantitative study, leveraging valuable insights gained during the qualitative phase. By systematically integrating findings from the qualitative analysis into the subsequent quantitative analysis, we aimed to enhance the overall depth and coherence of our study.

Step 4: Draw Meta-inferences from Mixed methods Results

The generation of high-quality meta-inferences relies on the effectiveness of data analysis in a study's qualitative and quantitative aspects (Venkatesh et al., 2013, 2016). As meta-inferences typically involve theoretical statements about a phenomenon, encompassing its interconnected elements and limitations, the process of inference development aligns conceptually with the formation of theory through observation (Venkatesh et al., 2013, 2016). This conceptual alignment underscores the flexibility in the development of inferences, which may traverse inductive, deductive, or abductive approaches. The choice among these approaches
is contingent upon the existence of theoretical foundations or conceptual frameworks guiding the study (Morse, 2010; Teddlie & Tashakkori, 2003). The theoretical underpinnings play a pivotal role in shaping the trajectory of inference development within the study’s analytical framework. Notably, the degree of theoretical grounding influences the depth and breadth of meta-inferences, allowing researchers to craft nuanced and contextually relevant theoretical statements that contribute to a more comprehensive understanding of the studied phenomenon.

**Theoretical Reasoning**

Our analytical approach is best characterized as abductive, as it initially embarked on an inductive path but underwent refinement through the integration of a pertinent theoretical framework that emerged as a highly effective guiding tool (Asatiani et al., 2021; Sarker et al., 2018; Tavory & Timmermans, 2014). The trajectory of our analysis began with an inductive exploration, allowing for the discovery of patterns and themes within the data. However, as the analysis progressed, the application of abductive reasoning became evident, especially in our emphasis on formulating and subsequently validating hypotheses. This transition was marked by the incorporation of a theoretical framework that not only provided structure to the emerging insights but also guided the interpretation and synthesis of findings (Further analysis details will be discussed in Chapter 4). The utilization of abductive reasoning in our analytical approach signifies a dynamic interplay between empirical observations and theoretical perspectives. This approach aligns with the notion that abductive reasoning involves inference to the best explanation, where the integration of theoretical constructs enhances the interpretive depth and coherence of the analysis (Asatiani et al., 2021; Sarker et al., 2018; Tavory & Timmermans, 2014). The theoretical framework, drawn from relevant literature and conceptual insights, served as a lens through which to view and make sense of the empirical data. This strategic blending of
inductive and abductive elements in our analytical journey illustrates the ongoing reflection and adjustment inherent in qualitative research, where theoretical considerations are crucial in refining and enriching the interpretation of findings.

Step 5: Assess the Quality of Meta-inferences

A comprehensive assessment of inference quality is crucial to elevating the quality of meta-inferences derived from both qualitative and quantitative components (Venkatesh et al., 2016). This evaluation should encompass key elements, including design quality, explanatory quality, and adherence to legitimacy criteria. This thorough evaluation ensures robust and reliable inferences, contributing to overall research credibility and understanding.

Inference Quality

To comprehensively evaluate the quality of meta-inferences in mixed-methods research, one should consider both design and explanatory quality (Tashakkori & Teddlie, 2003; Teddlie & Tashakkori, 2009; Venkatesh et al., 2013, 2016). Furthermore, Onwuegbuzie and Johnson (2006) offer a thorough typology encompassing nine legitimation types for mixed-methods research, including sample integration, inside-outside, weakness minimization, sequential, conversion, paradigmatic mixing, commensurability, multiple validities, and political legitimation. Onwuegbuzie and Johnson view legitimation as an ongoing process, assessing it at each stage of mixed research, diverging from Tashakkori and Teddlie's perspectives. Integrating Tashakkori and Teddlie's inference quality concept with Onwuegbuzie and Johnson's legitimation aspects enables a comprehensive assessment of mixed-methods study quality, incorporating both qualitative and quantitative standards. Legitimation types cover diverse dimensions, including statistical generalizations, insider perspectives, weakness compensation,
and minimizing potential impacts in sequential phases. Conversion assesses the interpretability of quantizing and qualitizing, while paradigmatic mixing evaluates the successful integration of paradigmatic assumptions. Commensurability necessitates iterative switching between qualitative and quantitative lenses, fostering a perspective beyond each in isolation. Multiple validities legitimation involves using varied research strategies to meet multiple validity criteria. Finally, political legitimation gauges the extent to which consumers value meta-inferences from both study components, suggesting strategies like employing multiple perspectives and generating practical theories for consumer value (Onwuegbuzie & Johnson, 2006; Venkatesh et al., 2016).

In our study, we adhered to established qualitative and quantitative standards to ensure the quality of our inferences. The legitimacy of our design and explanatory inference quality were evaluated through various types, including sample integration, inside-outside legitimation, multiple validities, and weakness minimization. We upheld qualitative inferences to the relevant qualitative standards and quantitative inferences to the appropriate quantitative standards.

Step 6: Discuss Potential Threats and Remedies

As discussed earlier, applying the legitimation framework introduced by Onwuegbuzie and Johnson (2006) facilitates the recognition of potential quality threats that may compromise the credibility of meta-inferences. Our study extensively addressed various limitations, considering threats related to sample integration and sequential legitimation. This comprehensive examination ensures a thorough understanding of potential challenges to inference quality in our research. These limitations will be discussed in the later chapters.
Summary

In summary, mixed methods constitute an invaluable methodological framework within the IS field. This approach's potency lies in its ability to effectively address the dynamic context of IS research by integrating quantitative precision and qualitative depth. By adopting mixed methods, we intend to unravel the complex factors influencing AI adoption within governmental auditing agencies, further enriching the collective understanding of technology implementation in diverse contexts.

3.3 Case Description (Organization Overview)

3.4.1 Differences Between Types of Organizations

Before discussing the organization chosen for this study, it is important to understand the differences between public, private, and government entities. In Saudi Arabia, the organizational landscape is characterized by a diverse array of entities, each serving distinct roles within the economy and society. Private organizations, public organizations, and government entities or agencies are the three primary institutions driving the nation’s development and governance. Understanding the differences among these types of organizations is crucial for appreciating their unique contributions and operational dynamics. This comparison explores the varying ownership structures, funding sources, decision-making processes, accountability mechanisms, profit motives, governance frameworks, and services provided by private organizations, public organizations, and government entities or agencies in Saudi Arabia. Table 3 Presents a comparison between these three types.
### Table 3. Comparison Between Types of Organizations in Saudi Arabia

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Private Organizations</th>
<th>Public Organizations</th>
<th>Government Entities/Agencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ownership</td>
<td>Owned by private individuals, families, or corporations</td>
<td>Owned by the government or public entities</td>
<td>Owned and operated by the government</td>
</tr>
<tr>
<td>Funding</td>
<td>Funded through private investments, loans, or profits</td>
<td>Funded through government allocations, taxes, and grants</td>
<td>Funded through government allocations, taxes, and fees</td>
</tr>
<tr>
<td>Decision-Making</td>
<td>Decisions made by owners, executives, or shareholders</td>
<td>Decisions made by management, board of directors, or stakeholders</td>
<td>Decisions made by government officials, ministries, and regulatory bodies</td>
</tr>
<tr>
<td>Accountability</td>
<td>Accountable to shareholders, regulatory bodies, and customers</td>
<td>Accountable to stakeholders, regulatory bodies, and the public</td>
<td>Accountable to citizens, legislative bodies, and oversight agencies</td>
</tr>
<tr>
<td>Profit Motive</td>
<td>Primarily profit-driven, with a focus on maximizing shareholder value</td>
<td>May have profit motive but also serve public interest or mission</td>
<td>Typically not profit-driven; focus on public service</td>
</tr>
<tr>
<td>Governance Structure</td>
<td>Determined by the organization's bylaws and management structure</td>
<td>Governed by a board of directors, executive leadership, or government officials</td>
<td>Governed by legislation, regulations, and bureaucratic structures</td>
</tr>
<tr>
<td>Services Provided</td>
<td>Products or services tailored to market demand</td>
<td>Services often include healthcare, education, infrastructure, public safety, etc.</td>
<td>Wide range of services spanning education, healthcare, defense, infrastructure, social services, regulatory functions, etc.</td>
</tr>
</tbody>
</table>

### Private Organizations

Private organizations in Saudi Arabia are owned by private individuals, families, or corporations. These entities are driven by the primary objective of generating profit for their owners or shareholders. Funding for private organizations typically comes from private investments, loans, and profits generated from their operations. The decision-making process is centralized around the owners, executives, or shareholders, who focus on strategies that maximize profits and ensure the long-term viability of the business. Private organizations are
accountable to their shareholders, regulatory bodies, and customers, balancing the need to meet financial targets with regulatory compliance and customer satisfaction. Examples of private organizations in Saudi Arabia include Jarir, Extra, and Al Rajhi Bank, which are significant contributors to the economy through various industries.

Public Organizations

The government or other public entities own public organizations in Saudi Arabia. These organizations are designed to serve public interests and provide essential services such as healthcare, education, infrastructure, and public safety. Funding for public organizations comes from government allocations, taxes, and grants, ensuring they have the financial support needed to operate effectively. Decision-making in public organizations involves management, a board of directors, or government officials, focusing on balancing financial sustainability and public service. Public organizations are accountable to stakeholders, regulatory bodies, and the general public, with their performance evaluated based on service quality and regulatory compliance. An example of a public organization in Saudi Arabia is the Saudi Electricity Company, which plays a crucial role in the public infrastructure and energy sectors.

Government Entities/Agencies

Government entities or agencies in Saudi Arabia are owned and operated by the government. Their primary objective is to manage and administer public policies, services, and regulations. Funding for these entities is provided through taxpayer money, fees, fines, and government allocations determined by legislative bodies. Decision-making within government entities or agencies is guided by government officials, ministries, and regulatory bodies, focusing on executing public policies and ensuring effective service delivery. These entities are
accountable to citizens, legislative bodies, and oversight agencies, emphasizing transparency and public resource management. Government entities or agencies provide various services, including education, healthcare, defense, infrastructure, social services, and regulatory functions. Examples include the Ministry of Education and the Ministry of Health, which oversee and manage public education and healthcare services.

Before concluding, it is essential to highlight the differences between various types of organizations concerning AI adoption and why government entities differ. In Saudi Arabia, the organizational landscape is diverse, comprising private organizations, public organizations, and government entities, each with distinct roles, mandates, and operational dynamics. The adoption of AI in government entities is shaped by their unique mandates, funding structures, and accountability mechanisms. Unlike private organizations, which are driven by profit motives and funded through private investments and operational profits, government entities primarily focus on public policy execution and effective service delivery. Their funding comes from taxpayer money, fees, fines, or government allocations, and they are accountable to citizens, legislative bodies, and oversight agencies (Dwivedi et al., 2021).

This focus on public service rather than profit necessitates tailored AI adoption strategies that align with government entities' specific operational and regulatory frameworks (Alotaibi & Alshehri, 2023). Such a strategy must consider the broader public interest, ensuring AI tools enhance transparency, accountability, and service quality. In contrast, private organizations may prioritize AI adoption for competitive advantage and efficiency gains, with decision-making centralized around owners or shareholders (Dwivedi et al., 2021).
Understanding these differences is crucial for optimizing AI integration across various organizational contexts. Effective and sustainable AI adoption in government entities requires approaches that address their distinct needs and constraints, emphasizing the enhancement of public services and adherence to regulatory standards (Wirtz et al., 2019). By recognizing these unique characteristics, policymakers and practitioners can develop more effective AI adoption strategies that improve operational efficiency and uphold the principles of good governance and public accountability (T. Q. Sun & Medaglia, 2019).

In conclusion, government entities and agencies in Saudi Arabia play a pivotal role in the administration and provision of essential public services. These entities are distinct in their ownership, funding, and operational mandates, being wholly owned and operated by the government. Their funding is derived from taxpayer money, fees, fines, and government allocations, ensuring they have the resources necessary to fulfill their public service mandates. Decision-making within these entities is driven by government officials, ministries, and regulatory bodies, emphasizing public policy execution and effective service delivery. Accountability is paramount, with government entities being answerable to citizens, legislative bodies, and oversight agencies. They provide comprehensive services, including education, healthcare, defense, infrastructure, and regulatory functions, essential for maintaining societal order and supporting economic development. Government entities, such as the Ministry of Education and the Ministry of Health, exemplify the commitment to enhancing the quality of life and well-being of the populace through dedicated public service.
3.4.2 The organization: SAB

The Supreme Audit Bureau (SAB) [Pseudonym] is the foremost audit entity within the Kingdom of Saudi Arabia, functioning with a distinct autonomous status and a direct reporting line to the King. With its primary focus on upholding financial accountability, the SAB undertakes a thorough post-audit examination encompassing critical aspects of the state's financial landscape, including assessing revenues, expenditures, and managing movable and fixed assets. Additionally, the SAB plays a pivotal role in promoting effective resource management, diligently overseeing the adherence of auditees to the stipulated financial and administrative regulations. Through this multifaceted mandate, the SAB ensures the transparency, prudent allocation, and responsible utilization of the kingdom's resources, thereby contributing significantly to maintaining fiscal integrity and regulatory compliance at a national level. SAB is a leading member of INTOSAI (International Organization of Supreme Audit Institutions).

The SAB's vision and mission statement precisely articulate its overarching aspirations and purpose. The Vision: SAB strives to attain institutional and digital excellence, establishing itself as a professional leader in safeguarding public funds. The Mission: The core mission of the SAB encompasses the comprehensive regulation of financial audits. This mission is intricately tied to enhancing the efficiency and quality of government entities' performance. The SAB's efforts extend towards seamless integration with audited entities, facilitating the elevation of institutional capacities and national competencies in the domains of the accounting and auditing professions. The SAB's vision and mission underscore its commitment to excellence, accountability, and holistic advancement within financial oversight and regulatory stewardship.
SAB’s core auditing functions involve Performance Audit, Financial and compliance audit, and Warehouse Inspection. We investigate them in the following subsections.

**Performance Audit**

SAB applies the concept of comprehensive audit, which encompasses performance audit aimed at independently evaluating the efficiency, effectiveness, and economical utilization of resources in programs or projects undertaken by auditees. This approach seeks to rectify deficiencies, enhance performance, and uphold compliance with regulations while fostering governance and transparency. The SAB's annual audit plans evaluate the performance of diverse government entities offering citizen services like education, healthcare, and municipalities. Furthermore, the SAB oversees companies with government investments, reporting findings to relevant entities for corrective actions and prevention strategies. In summary, a performance audit ensures that resources are employed efficiently and economically by the relevant auditee to attain the predetermined goals.

**Financial and Compliance Audit**

The primary aim of SAB is to conduct audits on all state funds and to ensure strict adherence to financial, administrative, and accounting regulations. A pivotal function of the SAB is financial and compliance audit, encompassing various aspects such as scrutinizing monthly accounting documents, contracts, warehouse records, revenues, funds, and collection procedures. The central objective of the SAB is to confirm the entities’ compliance with existing regulations, decisions, and instructions as they execute tasks, manage contracts, and implement project contracts and approved plans. This also involves verifying the accuracy of financial and accounting data, accounts, and records. Among the goals of this process are to validate the
appropriateness of financial transactions, ensure proper documentation, uphold adherence to applicable laws, verify proper accounting treatment in line with public accounting standards, ensure the presence of a robust internal audit system to safeguard public funds, and accurately reflect approved budget results in auditees' final accounts. The Financial and Compliance audit tasks include Audit Government Entities' Monthly Accounts Documents, Audit Government Entities' Final Accounts, Audit Government Contracts, Audit Financial Statements of Companies to which the State Contributes, and Revenues Audit.

Warehouse Inspection

The SAB's role involves examining the condition of government entities' warehouses to ensure the appropriate use of movable assets stored within and assess compliance with the Government Warehouse Rules and Procedures. This includes conducting annual sampling procedures on various types of warehouses such as car warehouses, spare parts storage, furniture repositories, electrical appliance facilities, medical supplies storerooms, and more. These audits encompass scrutinizing warehouse accounts and records, validating inventory, and reviewing registers submitted to the SAB. Additionally, the SAB is responsible for field audit missions related to government warehouses, focusing on resolving losses and damages within the government covenant and overseeing the associated financial implications.

3.4.3 The Auditees

The SAB’s auditees include the entire group of ministries, government entities, private enterprises, and the public corporations or bodies to which the State contributes to the share capital or guarantees a minimum profit.
The SAB’s auditing scope extends across a comprehensive spectrum of entities that collectively shape the economic and administrative landscape of the Kingdom of Saudi Arabia. This diverse array encompasses ministries, government entities, private enterprises, and public corporations. Within this intricate web of auditees, ministries are pivotal as central units responsible for formulating policies, implementing programs, and executing various governmental functions. Their operational significance necessitates diligent auditing to ensure the effective management of public resources and the accurate execution of public policies.

Furthermore, government entities constitute an integral segment of the auditee portfolio, representing specialized units with diverse functions ranging from healthcare and education to infrastructure development and public services delivery. Ensuring that these entities uphold financial integrity and adhere to regulatory guidelines is essential to maintaining the efficiency and integrity of public service provision.

In parallel, private enterprises, those of which the state holds a stake in terms of share capital or profit guarantees, contribute to the nation's economic fabric, serving as engines of growth, innovation, and employment generation. The SAB's oversight of these entities underscores the imperative of safeguarding fair competition, preventing fraud, and fostering an environment conducive to economic progress.

Lastly, public corporations and bodies are uniquely positioned within the auditee landscape. These entities span energy, telecommunications, and transportation sectors, impacting essential aspects of daily life. Thorough auditing of these bodies ensures their compliance with regulations and the effective management of public investments, promoting stability and accountability within these critical domains.
In conclusion, the SAB's expansive array of auditees collectively represents the intricate interplay of governmental, economic, and societal forces within Saudi Arabia. The meticulous auditing of ministries, government entities, private enterprises, and public corporations contributes to the nation's transparency, financial prudence, and sustainable growth.

3.4.4 GovAudit: Current Auditing System

As part of its digital transformation efforts, SAB has established an integrated electronic work environment to enhance communication and document exchange between the SAB and the entities subject to its audits. To this end, SAB has introduced the "GovAudit" electronic audit system [Pseudonym], which holds the capacity to automate various audit processes within the organization. An integral feature of GovAudit is its capability to facilitate seamless information sharing, fostering efficient interactions between SAB and the entities under its audit scope.

Furthermore, implementing GovAudit empowers SAB personnel to conduct financial reviews, analyze data, and process documents electronically. The outcome of audit activities is communicated electronically to the relevant authorities via the system, streamlining the process. Correspondingly, government agencies can respond to audit findings through the system, expediting the exchange of observations and insights. The electronic audit system, GovAudit, is structured around four key pillars: first, the establishment of streamlined data exchange mechanisms with audited entities; second, the provision of user-friendly avenues for data access; third, the empowerment of users to perform essential data analyses without specialized intervention; and fourth, an emphasis on extensive data analytics to inform the auditing process comprehensively.
GovAudit, SAB’s workflow system, audits state revenues and expenditures, monitors state fixed and current assets, ensures resource usage and preserves public funds. To monitor auditee performance and deploy resources efficiently, economically, and effectively to meet SAB’s aims and objectives. GovAudit is used by over 700 SAB auditors.

The "GovAudit" initiative encompasses a comprehensive set of objectives aimed at enhancing the efficiency, effectiveness, and accessibility of audit operations between SAB and the entities subject to its oversight. These goals include automating and optimizing audit services and processes, enabling a swift and secure exchange of information. The initiative seeks to establish a collaborative environment where audit programs can be developed and executed jointly by auditors and administrative personnel, ensuring a cohesive approach. Integral to this is the management and organization of auditees' data and records, streamlining the storage, retrieval, and tracking of audit tasks and results. By facilitating the preparation and tracking of auditee plans and activities, "GovAudit" contributes to proactive implementation monitoring.

The system is designed to harness authorized and secure channels for data exchange between SAB and its auditees, leveraging digital document management and archiving with stringent security standards. This transition toward digitization not only reduces paperwork and manual data entry but also promotes cost savings and operational efficiency. Additionally, "GovAudit" bolsters SAB’s audit reporting capabilities, enabling the generation of comprehensive reports while bolstering financial oversight to minimize wasteful expenditure. This initiative represents a shift from traditional data submission methods to raw data extraction from government platforms, fostering accuracy and transparency. Moreover, the system's analytical capabilities empower the SAB to categorize and analyze stored data over successive
fiscal years, yielding valuable insights, statistics, and comparisons that further strengthen its audit functions.

### 3.4.5 AI Implementation

<table>
<thead>
<tr>
<th>Who</th>
<th>Supreme Audit Bureau (SAB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>When</td>
<td>Implementing AI in 2025</td>
</tr>
<tr>
<td>Where</td>
<td>An Independent Governmental Organization in Saudi Arabia</td>
</tr>
<tr>
<td>Why</td>
<td>Planning to adopt AI to improve their KPIs (i.e. audit task completion rates)</td>
</tr>
<tr>
<td>How</td>
<td>By adding AI functionality to their current workflow system, “GovAudit”.</td>
</tr>
</tbody>
</table>

SAB plans to introduce AI in 2025 to transform the tasks handled by auditors in GovAudit and provide better analysis and insight capabilities (Table 4). The two main tasks that AI is transforming at SAB are Auditing and Inventory. These two tasks comprise most of the tasks being carried out by Auditors at SAB. They are planning to introduce it in two phases. The first phase will involve the introduction of a comprehensive Knowledge Management System using AI techniques to deal with documents and data and convert data into knowledge. The
second phase will include using a Robotic Auditor (RPA) to use AI techniques to automate work procedures and automatic audits through electronic robots.

Incorporating the Knowledge Management System marks the initiation of the initial phase, with a primary objective of leveraging artificial intelligence methodologies to handle documents and data effectively. This transformation process centers on converting raw data into valuable knowledge assets. The forthcoming outputs of the Knowledge Management System offer a comprehensive suite of benefits for the audit process. This entails optimizing the utilization of stored data, even those that are exempt from or not requiring auditing, thereby enhancing data-driven insights. The system's prowess in entity identification within documents expedites information retrieval, bolstering efficiency.

Moreover, its capacity to navigate and provide real-time access to the extensive registry of entities spanning governmental bodies, private enterprises, and individuals enriches auditors' resource pool. This seamless access facilitates potential audit expansion through streamlined information retrieval. The system's automated content comparison and matching capabilities further elevate the audit process, aligning theory with practical utility. In parallel, deriving statistics and reports on government agencies without exhaustive audits holds promise for informed decision-making and optimizing resource allocation. These envisioned Knowledge Management System outputs converge to revolutionize audits, harnessing artificial intelligence for knowledge extraction, process optimization, and heightened audit efficacy.

The second phase, centered around Robotic Process Automation (RPA), leverages artificial intelligence techniques to facilitate the automation of work processes and implement automated audits using electronic robots. SAB perceives RPA as highly advantageous in
auditing. RPA's ability to automate data collection and integration from various sources enhances accuracy and saves time. It automates repetitive tasks, allowing auditors to focus on more valuable activities and ensuring consistent and reliable audit processes. Additionally, RPA streamlines auditing and compliance procedures, increasing stakeholder satisfaction. Faster report delivery, improved fraud detection through pattern recognition, and the ability to compare data across systems further amplify the benefits of RPA. These advantages collectively enhance SAB's auditing practices' efficiency, accuracy, and effectiveness.
CHAPTER 4: PHASE I – Qualitative Component of the Study

In our qualitative research conducted within a governmental organization in Saudi Arabia, we set out to address a fundamental question: *What are the organizational factors that influence a governmental agency's inclination to incorporate AI into its existing workflow system?* To explore this inquiry, we conducted in-depth interviews with eight individuals affiliated with the governmental organization. It is worth noting that these participants were handpicked by the organization's management, serving as primary liaisons. The participants, either Team Leaders responsible for auditing functions or Auditors directly engaging with GovAudit, were integral to our investigation. We maintain that our qualitative sample is representative of the organization.

This section comprehensively details our data collection methods and the interview environment (Section 4.1). Subsequently, we elaborate on the ethical considerations that guided our research (Section 4.2). Following this, we thoroughly account for our data analysis and coding procedures (Section 4.3). In the subsequent section, we address data validity to ensure the credibility of our findings (Section 4.4). We then delve into the interview guideline questions and the initial findings gleaned from our interviews (Section 4.5). Finally, we present our conceptual model, marking the culmination of our primary objective in the first phase of our mixed-method research design: to identify the factors shaping the intention to adopt AI tools within governmental organizations in the context of auditing (Section 4.6). This comprehensive output will serve as the foundation for the quantitative component in the second phase of our mixed-method approach.
4.1 Data Collection and Interview Setting

We interviewed eight participants for this study: four Team Leaders with Auditing duties and four Auditors employed at SAB. These individuals were purposefully selected and nominated by SAB's management to participate in our research, given their roles and insights relevant to our study's focus. The interviews were conducted through online meetings via Zoom, which was chosen as the most suitable method, considering the COVID-19 pandemic in that period and its implications for in-person interactions. The interview sessions were thoughtfully scheduled at times convenient for the participants, each lasting at least one hour. The interview phase commenced on November 1st and concluded on November 24th, during which we conducted an average of two weekly interviews.

Our interview questions targeted both Team Leaders and Auditors at SAB, primarily focusing on their perspectives regarding AI's relevance and potential contributions to the organization's auditing processes (Check Appendix B for Interview details). We explored their understanding of AI, its anticipated impact on their roles, intentions regarding AI adoption in the workplace, concerns, perceived limitations of the existing systems, readiness for organizational transformation, and challenges encountered in this context. The interviewees were asked to provide deeper insights into SAB, including its functions, evolution, and specific concerns. Individual interview questions were designed to elicit their attitudes and intentions regarding AI integration in their work environment. Additional follow-up queries delved into their technology usage, both AI-related and conventional, and the advantages and disadvantages of AI implementation. Furthermore, we examined the overall work environment at SAB in order to understand the organizational context comprehensively.
Interviews continued until we reached theoretical saturation, signifying that further interviews did not yield novel insights. The semi-structured interviews were systematically recorded and subsequently transcribed and translated for analysis. This research offers valuable insights into the factors influencing the intention to adopt AI systems for auditing within a comprehensive organizational context. A detailed list of the interview questions can be found in Appendix A.

4.2 Ethical Considerations

We want to emphasize that this research was conducted with a strong commitment to ethical standards and the utmost consideration for participant privacy and confidentiality. We have proactively addressed potential ethical concerns or privacy risks associated with the research, the data collection methods, and our participants. Our interview protocol was designed in a way that does not elicit sensitive or private information from the interviewees. We maintained open communication with the designated contact point at SAB throughout the entry negotiation process, ensuring that we adhered to any necessary approvals or procedures required for conducting interviews.

To further safeguard the rights and privacy of our participants, we took several precautions. First, prior to the recorded interview, participants were required to confirm their understanding of and agreement with the consent form (see Appendix B). This form made it clear that participation was voluntary, and participants were not obligated to disclose personal information. They were informed that they could choose to skip any questions or withdraw from the interview at any point without incurring any risks or costs.
Second, we ensured that all information obtained during the interviews, whether in the form of notes or Zoom recordings, would be treated with the utmost confidentiality. To protect participant identities, we assigned specific ID numbers, denoted as "R#," with "R" signifying "Respondent" and "#" representing a number from 1 to 8.

Finally, all data collected during the interviews and the consent forms were securely stored in a cloud-based service with restricted access. Only the researchers in this study can access these files, ensuring their confidentiality and limited accessibility. These rigorous measures were implemented to uphold our participants' ethical principles and privacy rights throughout the research process.

4.3 Data Analysis and Coding

The authors did not receive approval from the government organization to send the Arabic-to-English translation and transcription of the interviews to a third-party organization. Therefore, the entire transcription process was managed internally. The interviews were initially transcribed in Arabic and subsequently translated into English by the primary author. While Arabic transcription tools were available, their effectiveness was limited due to the complexity of the Arabic dialect. Nevertheless, they provided a foundational structure for the author. The author then meticulously reviewed each interview, line by line, to rectify and improve translations where necessary. This comprehensive review led to significant revisions in various sections. The Arabic transcription was created, and translations were executed using the HappyScribe online tool, which was selected as the most suitable option for Arabic translation at the time. However, it is essential to emphasize that a thorough line-by-line revision was carried out, resulting in numerous corrections to ensure the utmost accuracy in the final transcripts.
Our analytical approach can be characterized as abductive. It initially followed an inductive path but was subsequently shaped by a relevant theoretical framework that emerged as an effective guiding tool (Asatiani et al., 2021; Sarker et al., 2018; Tavory & Timmermans, 2014). In studies of this nature, theory introduction typically occurs after the initial 1st level coding, enabling researchers to identify an appropriate theory inferred from the data. As a result, our subsequent coding of higher-level concepts (2nd and 3rd levels) was informed by these theories, influencing the direction of our analysis. By leveraging the qualitative data and existing theory, we were better equipped to uncover higher-level concepts and abduct causal relationships, enriching our overall research process.

We began the coding process without pre-established codes, allowing the data to shape our coding. We utilized constant comparative analysis to identify initial concepts and establish links between these emerging ideas and more abstract categories, mirroring the open coding phase of grounded theory (Charmaz, 2000; B. G. Glaser, 1992; B. Glaser & Strauss, 1967). The open coding process involved several steps: Initially, we generated a list of primary codes from the data using Atlas.ti software. Then, after a thorough review of translated transcripts, we formulated "abstract categories" by assigning labels to recurring observations with commonalities (Miles & Huberman, 1994). Previous research (Sarker et al., 2002) affirmed that exclusively employing the open coding phase is valid. In Appendix C, we present the primary open codes, indicating which respondents referred to each concept, and we highlight the higher-level categories derived from these open codes. In Appendix D, we provide illustrative quotations for each open code. The selection of these two illustrative examples was motivated by (Wunderlich et al., 2019) research.
Our research methodology was underpinned by a methodical, multi-phased coding approach that enabled us to extract meaningful insights from the collected data. We initiated our analysis with the open coding phase, emphasizing a strict grounding in the data. We refrained from superimposing preconceived categories or labels onto the information during this preliminary stage. Instead, we allowed the data to organically steer our coding process, enabling us to identify and label key concepts and patterns as they naturally manifested from the raw dataset. Open coding served as the cornerstone of our analytical framework, providing a solid foundation for our subsequent investigative stages. In this initial phase, we generated 255 first-level codes, reflecting the richness and complexity of the data. However, recognizing the need for further refinement and synthesis, we diligently reviewed and examined these codes, uncovering their commonalities and connections. This meticulous review and analysis resulted in a more focused set of 155 first-level codes (including demographic-related data codes), providing a more streamlined and coherent representation of the data.

Expanding upon the foundation laid during the open coding phase, we seamlessly transitioned into the axial coding stage of our analysis. This pivotal phase was instrumental in unearthing the connections and interrelationships between the initial codes and concepts we had meticulously identified through open coding. Axial coding served as a dynamic process through which we sought to elucidate the emerging themes and patterns beginning to surface within our dataset. With axial coding, our focus shifted towards a deeper exploration of the intricate details inherent in the data. Through this phase, we organized our data into coherent clusters, giving rise to a more nuanced comprehension of the underlying themes and dynamics. To facilitate this process, we introduced categorical codes, which effectively accommodated the first-level codes. These categorical codes were thoughtfully grouped based on the relevance of the factors they
encapsulated, culminating in the creation of 16 distinct second-level codes. This hierarchical structuring allowed us to dissect the data with greater precision and granularity, ultimately enhancing the clarity and depth of our analysis.

In pursuing a more refined and comprehensive understanding of the data, we undertook the crucial phase of theoretical coding. This final coding stage exceeded the specific instances and themes unveiled during the prior open and axial coding phases. Instead, it involved the creation of higher-level codes that could effectively encapsulate the overarching concepts and theoretical insights that permeated our dataset. As we delved into the data, it became evident that the TOE framework was the most suitable theoretical framework to encompass our codes, providing a robust structural foundation for our analysis. Additionally, TTF theory proved invaluable in providing context for the task and technology-related codes within the context of auditing practices.

By engaging in theoretical coding, our goal was to synthesize our findings and abstract the fundamental principles and patterns that lay at the heart of our dataset. This systematic application of theoretical coding enabled us to forge connections and extract higher-level codes that transcended individual data points, ultimately leading to a more profound comprehension of the phenomena we were investigating. The meticulous nature of this coding process was essential in ensuring the rigor and depth of our analysis. It facilitated our ability to draw meaningful conclusions from the data, enriching the quality and validity of our research. A list of the codes generated is available in Appendix E.
4.4 Validity

In research, the diligent consideration of validity issues is essential to uphold the integrity and reliability of a study (Bryant, 2000). Our research methodology relied on semi-structured interviews to gather data. Given the unique context of our study within a governmental organization, potential sources of bias should not be underestimated. Respondent bias, researcher bias, and self-reporting bias (Li et al., 2016; Scott et al., 2015) may come into play, particularly when participants harbor concerns about the implications of AI for their roles, job security, or the need for additional training, especially among those who may not be technologically adept. Despite the purposeful selection of participants orchestrated by the governmental organization, we deliberately avoided leading questions, ensuring respondents could freely express their views and perspectives. We also reassured interviewees that our research maintained a neutral stance, emphasizing the confidentiality of the findings, thereby preventing any potential influence on their responses.

A second validity issue of significance is reactivity (Maxwell, 2012), which assumes importance due to the organizational setting of a government entity. Reactivity refers to the possibility of participants altering their behavior or responses due to their awareness of being observed or studied. In the context of government employees, reactivity becomes a critical concern. The knowledge of being part of a study can induce changes in behavior, responses, or attitudes. To mitigate this, we explicitly communicated to our participants the confidentiality of the study, stressed its non-evaluative nature, and avoided guiding participants on what to say or how to express their thoughts.
To further bolster our research's validity and diminish the potential influence of bias and validity threats, we meticulously cross-verified responses and coded independently from all interviews, aligning them with the intended perspectives laid out in our codebook. Additionally, we established an open channel for member checks with our participants (Lincoln & Guba, 1985), a process enabling us to obtain feedback that ensured our interpretation of the collected data faithfully represented the participants’ intended meanings, thus minimizing the risk of misinterpretation.

It's important to note that our study may not serve as a direct example for measuring external validity. Still, it stands as a valuable source for inferring potential outcomes in similar governmental organizations sharing similar contexts and settings (Jayatilleke & Lai, 2018). This study's findings offer insights that can be applied to diverse governmental bodies grappling with comparable challenges and opportunities related to AI adoption.

4.5 Interview Questions and Initial Findings

This section provides a comprehensive overview of the interview questions directed at the participants, along with a presentation of the initial findings. These findings have been systematically categorized based on the interview guidelines outlined in Appendix A, primarily for illustrative purposes and to facilitate a clear presentation. It is important to note that this categorization was not utilized to inform the coding process itself. These findings serve as a cornerstone in shaping the construction of our conceptual model, as they are directly derived from the qualitative data gathered during this research phase.
4.5.1 Demographic

As for the demographic details, all participants in this study were carefully selected by SAB’s management, ensuring a diverse representation of the organization. The cohort was comprised of four Team Leaders and four auditors, each working in distinct departments within SAB. Notably, all participants in this study were male, representing a specific demographic composition. Regarding age distribution, four participants fell within the 30-40 age group, three in the 50-60 age bracket, and one between 40-50. The educational background of all participants indicated a consistent attainment of at least a bachelor's degree, with only one individual holding a master's degree. Notably, the participant with a master's degree had pursued their higher education abroad, while the remaining participants had completed their education locally. When examining the participants' job experience at SAB, three individuals boasted more than 30 years of dedicated service, two had accrued over 15 years, and three had less than 15 years of SAB work experience. It's worth highlighting that only three employees had additional work experience beyond their tenure at SAB, and this was predominantly among those with less than 15 years of experience within the organization.

4.5.2 Current System “GovAudit”

In this section, our inquiries were centered on the participants' perceptions of the current system, "GovAudit," employed for handling auditing tasks within SAB. The outcomes regarding the advantages of using GovAudit revealed a unanimous consensus among all participants. They acknowledged a significant reduction in the reliance on physical paper documents, with GovAudit enabling the seamless exchange of digital PDF audit files between SAB and external agencies. Additionally, a majority expressed satisfaction with the automatic storage of their work
in the system, which could be accessed from any location and at any time, eliminating the need for physical document filing and retrieval. Furthermore, several participants attested to GovAudit’s role in simplifying their work processes, enhancing efficiency, and expediting operations.

[R2] *GovAudit today has many services, including organizing work, defining tasks, keeping files, reviewing reports, directly communicating with the authorities, and documenting work papers.*

Conversely, the disadvantages of using GovAudit primarily revolved around issues related to third-party integration, communication, and cooperation. Participants highlighted challenges such as third-party organizations deviating from the system’s prescribed processes when submitting audits and contracts. These challenges included sending documents in different formats, omitting documents, addressing them to the wrong recipients, personnel changes within third-party organizations responsible for communication with SAB, and the necessity of ongoing education on system usage. A subset of auditors also observed limitations within the system, particularly the absence of functions for highlighting specific areas of interest in documents and the lack of automated reminder features for auditors in cases where third-party organizations failed to resolve issues within specified timeframes. One decision-maker noted a critical limitation concerning the size of PDF files, foreseeing exponential growth in storage requirements due to the increasing reliance on PDFs. Consequently, SAB is in the process of implementing a raw data format for exchanges with third-party organizations during their AI transformation.
For example, some government agencies now refuse to associate with us because of how our GovAudit system is linked to the internet. They prefer not to connect to any system associated with the Internet. This policy is enforced from their end, granting them the right to dictate these terms. However, if we were to shut down the system on an internal network, it would reduce services provided by GovAudit.

Regarding satisfaction levels, participants generally reported moderate satisfaction with GovAudit, with reduced paper usage being the most commendable feature. Regarding current technological factors influencing job performance, all participants expressed contentment with the tools currently in use, except for one auditor who cited concerns about the speed and performance of their hardware. Overall, the responses of auditors and Team Leaders demonstrated a notable similarity in their perspectives on GovAudit.

4.4.3 Perception of AI

In this section, we explored the participants’ perceptions of AI and their expectations for its implementation at SAB. Notably, all the Team Leaders exhibited a proficient understanding of AI, demonstrating a strong grasp of its capabilities. They frequently likened AI to a technology with human-like capabilities, emphasizing its potential to handle tasks without being burdened by workload and to excel in complex analytical tasks. Moreover, these Team Leaders showcased knowledge about different types of AI, including machine learning.

This implies interaction with an intelligent program. It potentially offers insights into the overall administration, evaluating an employee’s proficiency and work status. This intelligent system can facilitate communication, verify details like licenses and pending tasks, and enable efficient transaction handling by competent employees.
Conversely, the auditors exhibited relatively moderate knowledge of AI, with only one participant lacking a clear understanding of its meaning. They often associated AI with entities like Google and AI commonly found in video games. When inquired about their awareness of the AI transformation process at SAB, all participants were well-informed about these plans before the interview. This observation underscores the effectiveness of communication within SAB, particularly top-level executives' proficiency in conveying digital transformation initiatives to the workforce. Furthermore, several Team Leaders expressed interest in how the AI system would facilitate the learning and processing of big data. This keen interest hints at the potential role of AI in driving a positive transformation of the existing GovAudit system within SAB.

4.5.4 AI Innovation

In this section, we delved into our participants' expectations regarding using AI in auditing and their optimism concerning its integration into their daily tasks. A striking consensus emerged as most participants expressed optimism about AI significantly expediting the processing of audit documents. They believed the AI system would empower them by handling the heavy lifting, leading to more efficient processing and enhanced document analysis. Moreover, they anticipated the system would guide them by identifying areas of interest in documents, eliminating the need for manual scrutiny and issue identification. This consensus revolved around the overarching benefits of reduced workload and improved analysis, underlining the participants' shared enthusiasm for AI integration. Additionally, one auditor anticipated that the new system would either eliminate or substantially reduce the errors typically associated with human auditors.
Presently, the Bureau encounters a significant challenge in familiarizing itself with all government agencies on an annual basis. This necessitates each competent department to scrutinize its subsidiaries annually, a task hampered by the Bureau's limited workforce and the extensive number of authorities. However, this predicament is on the verge of resolution. The activation of artificial intelligence tools, when executed accurately, professionally, and with high quality, holds the promise of transforming this annual ordeal. With these tools in play, the Bureau envisions a monthly review cycle for all parties involved, a substantial improvement over the current yearly assessment.

Surprisingly, three of the Team Leaders expressed the view that there were no downsides to using AI. This perspective was unexpected, considering their acceptable knowledge of AI, which led us to assume that they might be aware of potential transparency and bias issues associated with AI utilization. The one decision-maker who did cite potential negatives raised several thought-provoking concerns, including the misuse of technology, security implications necessitating system restrictions, integration challenges with third-party organizations, privacy issues, and potential adjustments to GovAudit's accessibility. Notably, the concern regarding the misuse of technology centered on the belief that employees might become overly reliant on AI-generated outcomes, potentially sidelining their due diligence.

In specific contexts, there is a concern regarding the inappropriate use of artificial intelligence in particular applications.

Among the auditors, three cited hacking and data breaches as concerns associated with AI usage. This alignment with expectations was attributed to their relatively limited understanding of AI. However, one auditor expressed unease about a system responsible for comprehensive
analysis. When we probed about their trust in the transparency of AI-generated outcomes, all participants expressed confidence from their perspective despite recognizing potential trust issues with third-party organizations relying on AI results. In terms of their optimism, all participants showed strong support for implementing AI at SAB and anticipated that it would contribute to successfully completing objectives across all departments.

4.5.5 Organizational Impact

In this section, we engaged our participants in discussing the notable impediments to implementing new technology, particularly AI, at SAB and its potential organizational impact. We also probed their perceptions of governmental support for such technology within the context of Saudi Arabia. The responses we garnered presented a diverse array of barriers to AI implementation. One Auditor and one Decision-maker identified Resistance to change as a potential obstacle, suggesting that some individuals within the organization may be apprehensive about transitioning to AI. However, another Decision-maker took an opposing view, asserting that resistance to change is an outdated concern and would not hinder the shift to an AI system. Several participants cited the steep learning curve associated with new technology as a barrier that could affect performance. To address this issue, they recommended providing educational courses to familiarize employees with the technology before its implementation. Furthermore, one Auditor expressed uncertainty regarding the management's guidance on the AI implementation plan, emphasizing a need for more clarity about expectations.

[R1] Currently, there are no specific courses on artificial intelligence available. However, the Bureau is actively committed to employee development through continuous courses, exemplified by the establishment of a dedicated center for financial auditing and
performance control, colloquially referred to as the "training" center. While this center primarily focuses on training Bureau employees and those from external organizations, there hasn't been a dedicated course on artificial intelligence yet. Nonetheless, a current study and ongoing discussions demonstrate a keen interest in this field, signaling the Bureau's commitment to advancing its workforce in artificial intelligence.

The barriers outlined by the participants are well within the norm, given the intricacies and nuances of the implementation process. Additionally, our investigation extended to governmental support for AI implementation in the Kingdom of Saudi Arabia. Six of the participants indicated their belief in the existence of robust governmental support for AI adoption across all government agencies. Their belief stemmed from observable changes within the Kingdom and the information they had encountered. Interestingly, the two participants who did not perceive governmental support for AI included an Auditor and a Decision-maker, each representing different age groups (30-40 and 50-60, respectively). Notably, both individuals had exclusively worked within SAB, adding an intriguing layer to this finding.

4.5.6 Implementation Readiness

In this section, we delved into the participants' perceptions regarding SAB's readiness for AI implementation and identified potential factors that could impede the process. Surprisingly, only three participants, one Auditor, and two Team Leaders, expressed confidence in SAB's readiness to implement AI. Conversely, the majority believed that more time is required for SAB to prepare for AI integration fully. Some echoed the sentiment that while the digital transformation unit appears prepared, limitations exist regarding available resources, particularly budgetary constraints. This perspective suggests that the current budget allocation might need to
be commensurate with the demands of the transformation process, potentially hindering its seamless execution. However, others don’t see budgeting as an issue.

[R1] While harboring significant ambitions, the realization of such goals is contingent on resource availability. Presently, there is substantial support for these aspirations, which is notably evident at the state level in digital transformation. This support is integral to realizing key programs outlined in the Saudi vision and bolsters digital transformation nationwide. The implementation of artificial intelligence in our Bureau is subject to a pragmatic approach, with the timeline tethered to the constraints of the available budget.
CHAPTER 5: CONCEPTUAL MODEL

The qualitative findings aim to identify the factors that will undergo testing in the subsequent quantitative phase of our mixed-method research. In shaping our conceptual model, we adopted a structured approach. First, we employed the TOE framework as the foundational theory, providing insights into the primary variables influencing the intention to adopt AI tools. Second, we integrated perspectives from the DOI and TTF theories to enrich the relationships within our conceptual model. Third, we utilized qualitative data to pinpoint the specific constructs that impact the intention to adopt. Finally, we drew upon the qualitative data and relevant literature associated with the theories to formulate and substantiate our hypotheses. The hypotheses presented are categorized according to the TOE framework, which includes the DOI-specific constructs in the technological factors and the TTF framework (Figure 7).
Perceived AI Complexity

Complexity refers to the degree to which an innovation is perceived as difficult to understand and use, and it is often considered a significant barrier to adoption (Rogers, 1995). Previous research on adoption has consistently shown that complexity negatively impacts the willingness of individuals or organizations to adopt a new technology (Picoto et al., 2014; Rogers, 1995; Wright et al., 2017; Z. Yang et al., 2013).
In line with these findings, the results of our qualitative study also indicate that complexity plays a crucial role in hindering the adoption of a new system at SAB. The current system presents several challenges for auditors, from the complexity of their chain of task operations to difficulties using the system and an unhelpful user interface. These factors collectively limit the auditors' abilities to perform their tasks efficiently and effectively, as demonstrated by the following quote:

“I mean, there is a need for some improvement to the icons in GovAudit. Some things are technically possible, but some icons are unclear to the recipients or the employees working on GovAudit. Some colleagues may experience confusion, make mistakes, or be ignorant of the system's mechanism. The complexity in the chain of audit task operations of GovAudit poses quite a challenge as well.” [R4]

During the interviews, all participants expressed a common sentiment: They hoped that the integration of AI would lead to a comprehensive overhaul of the current system, simplifying the process and addressing the issues caused by minor complexities. They believed that a more streamlined and user-friendly system, aided by AI capabilities, would enhance their productivity and enable them to carry out their tasks with greater ease and accuracy.

By addressing the complexity barrier and introducing an intuitive and easy-to-navigate AI-augmented system, SAB can facilitate the successful adoption of the new technology, thereby improving the overall efficiency and effectiveness of the auditing processes. The potential for simplified tasks and increased user-friendliness could foster a positive attitude toward adopting AI among auditors, leading to higher engagement and utilization of innovative technology for the task at hand. Therefore, we propose the following:
H1: AI complexity negatively influences the Task-Technology Fit.

Perceived Scalability

Scalability, as defined by Weyuker & Avritzer (2002), refers to the system's capability to efficiently expand its capacity by adopting a cost-effective strategy, enabling it to handle an increased workload effectively. The core purpose of scalability is establishing a sustainable, repeatable solution for capacity creation rather than focusing solely on one-time capacity increases (C. Sharma et al., 2023).

In our study, we explore the perceived scalability of AI tools in handling the significant workload of auditing tasks at SAB and achieving high task completion rates. Our interviewees express their anticipation that the introduction of AI tools at SAB will empower them to accomplish a greater number of tasks within a shorter period than they typically manage, as demonstrated in the following quote:

“Today, one of the challenges the Bureau faces is the difficulty of familiarizing itself with all government agencies annually [For audit purposes]. This entails an annual review, with each competent department being obligated to assess its subsidiaries. The task becomes daunting due to the vast number of authorities [to audit] and the limited number of employees at the Bureau. However, this limitation is set to be entirely overcome if the artificial intelligence tools are properly, professionally, and effectively activated. With the correct implementation of AI, it becomes feasible to review all parties every month rather than once a year.” [R1]
This understanding of scalability underscores the importance of AI technology in facilitating enhanced productivity and efficiency within the audit processes at SAB. Integrating AI tools can significantly impact the organization's effectiveness and responsiveness to increasing demands by providing a sustainable and adaptable approach to capacity creation. Integrating AI tools, which offer a sustainable and adaptable approach to capacity creation, signifies a positive task-technology fit. As these AI tools can efficiently handle the significant workload of auditing tasks and improve task completion rates, they address the specific demands and requirements of SAB's auditing processes. This alignment between the AI technology and the organization's tasks leads to enhanced effectiveness and responsiveness, ultimately contributing to a successful task-technology fit.

In summary, the focus on scalability and integrating AI tools in audit processes at SAB highlights the relevance of task-technology fit, as the technology's capabilities align with and support the organization's specific tasks and objectives. Therefore, we propose the following:

H2: Perceived Scalability positively influences the Task-Technology Fit

Relative Advantage

Relative advantage is the degree to which innovation, such as AI technology in Auditing, is perceived as providing greater benefits than its alternatives that are currently in place (Molinillo & Japutra, 2017; Picoto et al., 2014; Rogers, 1995). In our context, Relative advantage focuses on how the AI tool outperforms the current auditing methods at SAB in terms of accuracy, efficiency, and the value it adds to the audit process by enabling more in-depth analysis and more reliable results. Many prior adoption studies have identified that relative advantage influences adoption decisions (Alsheibani, Messom, & Messom, 2020; Jeyaraj et al.,
2006; Kim et al., 2018; Picoto et al., 2014; C. Sharma et al., 2023; Venkatesh & Davis, 2000; Wright et al., 2017; Z. Yang et al., 2013; Zhu et al., 2006). For auditing tools, such as RPA, the relative advantage of using them increases auditor productivity and the quality of their work (C. Sharma et al., 2023). The results of our qualitative study echo this finding by establishing that the auditors in our study are positively influenced by what they will gain from using this technology. The interviewees perceive that with AI Tools, they will have better data analysis capabilities, automation of audit tasks, reduction of auditor error rate, improvement in the audit quality, and ultimately lead to better decision-making capabilities as demonstrated by the following quote:

“I mean, developing very advanced technical tools and, of course, incorporating artificial intelligence will result in a smart system capable of providing genuinely useful results in the audit reports. These outcomes are undoubtedly reflected, and, in the end, they greatly assist the decision-maker and the decision-making process.” [R2]

The connection between "Relative Advantage" and "Task-Technology Fit" is evident in the considerations made by auditors and Team Leaders from our qualitative findings. The ability of the AI tool to identify anomalies and patterns in financial data more effectively and perform complex calculations rapidly indicates its superiority in enhancing the efficiency and accuracy of the audit process, thus presenting a positive relative advantage over the current approach at SAB. Additionally, the tool's potential to automate repetitive tasks contributes to its favorable relative advantage, as it saves time and resources for auditors. Therefore, the relative advantage of the AI auditing tool is closely related to its "task-technology fit," as it aligns well with the specific tasks and needs of auditors and Team Leaders, providing a technologically superior and efficient solution to their requirements. Therefore, we propose the following:
H3: Relative Advantage positively influences the Task-Technology Fit

Security

The degree to which a platform is perceived as unsecured for exchanging data and executing transactions is defined as a security risk (Zhu et al., 2006). Existing literature on organizational adoption has identified security as a critical factor that could significantly impact the intention to adopt AI in various contexts (Alsheiabni et al., 2019; Pillai & Sivathanu, 2020). In the case of AI, we specifically refer to AI’s security concerns as the risk associated with using a highly intelligent system. Based on our qualitative findings, we find that a governmental auditing agency responsible for overseeing many different private and public agencies in the Kingdom of Saudi Arabia may be vulnerable to such AI security concerns. While there is a consensus that security measures are in place to safeguard the organization, a few of our interviewees expressed concern about the potential risks associated with an AI system handling the entire analysis in auditing. They worry that such a system could become susceptible to cyber-attacks or hacking, as demonstrated by the following quote:

"I am not afraid of security concerns that much, except in the case of hacking or cyber espionage." [R5]

Therefore, it is worth exploring the aspect of security in greater depth and examining the consensus among other auditors at SAB to understand their views and feelings about the security measures currently in place. Therefore, we propose the following:

H4: Security concerns will influence the intention to adopt AI.
5.2 Organizational Leadership Support

Top management's crucial role in the AI adoption process is evident through their explicit and active assistance to the organization during the introduction phase. Their involvement and commitment motivate employees to overcome employee resistance (Pillai & Sivathanu, 2020; Vasiljeva et al., 2021). Research highlights top management support as the key link between organizational IT adoption and individual adoption of IT innovations (Jeyaraj et al., 2006).

In the AI adoption literature, the role of top management has been identified as a success factor in various contexts and industries (H. Chen, 2019; Chen et al., 2023; Gupta et al., 2022; Horani et al., 2023; Jadhav, 2021; Phuoc, 2022; Pillai & Sivathanu, 2020; Rawashdeh et al., 2022; C. Sharma et al., 2023; Vasiljeva et al., 2021). In our specific context, we refer to top management support as Leadership support due to the organization's unique context being a governmental bureau agency, where top management is referred to as leaders, including the heads of department and the president of SAB.

The findings from our qualitative study validate this predictor of AI adoption. Our interviewees have expressed that they feel highly supported by the Leadership at SAB in the ongoing AI adoption process. Moreover, they sense that the leadership actively promotes a feedback-driven culture and has effectively planned and committed to AI adoption. The interviewees have shown complete trust in the leadership's commitment and planning for AI adoption. They also perceive the AI integration and overhaul of the current system as beneficial, which has positively influenced their perception of the upcoming AI implementation, as demonstrated by the following quote:
“There is ample support, and we hold nearly monthly meetings, the most recent of which aimed to encourage and endorse artificial intelligence adoption with His Excellency the President, who is eager to achieve a fully AI-driven work environment.” [R5]

In conclusion, the crucial role the Leadership will play in the AI adoption process cannot be overstated. Their explicit and active support will act as a driving force in overcoming employee resistance and fostering a positive attitude toward AI adoption. As the organization continues its AI adoption, the ongoing commitment and involvement of the leadership will play a pivotal role in ensuring the successful integration of AI technologies and reaping their benefits across the organization. Therefore, we propose the following:

**H5: Leadership support positively influences the intention to adopt AI tools.**

Organizational Readiness

Organizational readiness pertains to the organization's preparedness in terms of financial resources, human capital, and infrastructure to embrace and implement new IT innovations (Wiggins et al., 2020). This readiness encompasses a robust IT infrastructure, the allocation of financial resources to support new IT innovations, and the presence of skilled and knowledgeable employees, all essential factors influencing the adoption of new technologies (Zhu and Kraemer, 2005). In the case of AI adoption, auditing organizations are facing challenges primarily due to their limited grasp of AI capabilities, inadequate skills, unavailability of off-the-shelf AI tools, and financial constraints, impeding their ability to invest in AI adoption (Seethamraju & Hecimovic, 2022). Our qualitative findings align with existing literature, underscoring the crucial role of organizational readiness in successful AI adoption.
Regarding the technical capability of auditors, our interviewees revealed that a significant portion of the staff needs more technical proficiency, particularly among older employees who frequently seek assistance from their younger counterparts. This suggests that the current workforce may need to be adequately prepared for the transformative impact of AI adoption. An Exemplar quote is presented below:

“For instance, similar to my father, who is not accustomed to using technology and requires my assistance for basic tasks, elderly individuals in the Bureau also face similar challenges and fears regarding technology. Consequently, they often seek the support of young, technically proficient employees. This reliance on younger colleagues remains their primary recourse in navigating technological aspects, as they may lack familiarity and comfort with modern technologies.” [R7]

Examining the financial readiness aspect, our qualitative data presents mixed results regarding SAB's preparedness for AI adoption based on its budget. While there is governmental support for this adoption, it was surprising to observe varying sentiments among auditors and Team Leaders regarding their readiness to embrace AI. An Exemplar quote is presented below:

“I think it is a very big ambition [Adopting an AI tool], but of course, the resources may not always be available.” [R2] “According to the current GovAudit system, we can say that it is not fully ready in terms of budgets. However, in terms of work, it is currently underway with the efforts of the leadership at SAB, and we are looking forward to improvements soon.” [R1]
From a technical infrastructure perspective, the qualitative data highlights several challenges faced by SAB. These include connectivity issues with other agencies, limitations in the database due to the large size of current files, and the necessity for suitable data to enable the AI tool to function effectively. An Exemplar quote is presented below:

“The first issue is a technical defect, which means that sometimes the system stops due to various reasons, and this interruption in communication between us and government agencies can occur for reasons beyond our control. It could be related to the network of the government agency itself or the Bureau's network. These are some of the problems that can occur.” [R8]

In summary, our research emphasizes the significance of organizational readiness in AI adoption endeavors. It underscores the need for financial investment, technical competence, and supportive infrastructure to integrate AI technologies within the organization successfully. Addressing these factors will facilitate a seamless transition and enable organizations to leverage the full potential of AI to achieve their objectives. Therefore, we propose the following:

**H6: Organizational Readiness positively influences intention to Adopt AI.**

AI Strategic Alignment

IT strategic alignment involves integrating an organization's IT initiatives, resources, and capabilities with its overall business strategy, ensuring that IT investments and solutions support achieving its goals and objectives (Henderson & Venkatraman, 1999). Similarly, AI strategic alignment refers to aligning an organization's strategic objectives with adopting and
implementing AI technologies and integrating AI initiatives into the broader business strategy to achieve long-term success and competitive advantage (Horani et al., 2023).

By achieving AI strategic alignment, organizations can harness the potential of AI to drive innovation, enhance decision-making, improve operational efficiency, and achieve desired outcomes. However, our qualitative findings indicate that Auditors expect a cautious and gradual introduction of AI tools into GovAudit based on their prior experience with innovations. While some expressed uncertainty about the impact on their current job roles, the majority appear open to the introduction, acknowledging the importance of clear guidelines and planning before AI adoption. Addressing employee resistance and ensuring the presence of AI regulation and methodology prior to adoption is critical to mitigating fears.

The artificial intelligence vision must be very clear. What is the future plan? I mean, will artificial intelligence be a long-term solution? Or is it just a trial period to gauge its effectiveness and importance for us auditors and our roles? Furthermore, what if we encounter some mistakes or find it unsuitable? Perhaps we should consider an alternative approach. [R4]

Our findings are consistent with other organizational auditing adoption studies that also highlight AI strategy as a key factor in AI adoption (Alsheibani, Messom, & Messom, 2020; Rawashdeh et al., 2022; J. Yang et al., 2021). This underscores the importance of a well-defined strategic plan for successful AI integration. By aligning AI initiatives with the overall business strategy, organizations can harness the full potential of AI to drive innovation, improve efficiency, and achieve their strategic objectives. A well-defined AI strategic plan for AI adoption, transparency between employees and business leaders, and a clear understanding of the
organization's IT capabilities are essential components in achieving successful AI adoption and maximizing the benefits of AI across the organization. Therefore, we propose the following:

**H7: AI Strategic Alignment positively influences the intention to adopt AI.**

**AI Awareness**

AI awareness refers to the level of understanding and knowledge that individuals or employees have about the various cognitive functions of AI (Hofmann et al., 2020). These cognitive functions include capabilities such as perceiving information from the environment, predicting future outcomes based on data analysis, and generating new content or insights. This understanding enables employees to perceive AI as a versatile tool and recognize its potential applications in their specific industry or context (Jöhnk et al., 2021). By being aware of the cognitive functions of AI, individuals can better leverage its capabilities and make informed decisions on how to incorporate AI into their work processes or business strategies.

In the adoption literature, AI awareness was found as a sub-category of managerial obstacles that affect adoption (Alsheibani, Messom, & Messom, 2020). They also found that AI awareness can be a contributing factor to the adoption process, arguing that a lack of clarity in terms of what AI can be used for in organizations, as well as a lack of access to new skills to analyze, design, and implement AI solutions, can hinder AI adoption. Furthermore, other AI adoption work includes the factor of AI Awareness in firm readiness, IT readiness, and organizational readiness in the organizational dimension, which includes different factors like technology competence and organizational and technical infrastructure (Alsheibani et al., 2018; Jöhnk et al., 2021; Rawashdeh et al., 2022; J. Yang et al., 2021). Based on our qualitative data
findings, we argue that this factor should be clearly distinguished from others and tested on its effect on the intention to adopt AI.

According to our findings, a lack of knowledge of AI can impede AI adoption in some circumstances. The factor of AI awareness refers to our auditors’ knowledge about AI and how they might define or associate it. From our qualitative data, we found a contrast between the auditors and Team Leaders in defining AI, as demonstrated by the following quotes when asked about how they would define AI:

“I have not extensively read about the field of artificial intelligence, but what I know is like the Google search engine.” [R7]

“Well, our use of AI in accessing Google. For instance, if I have a specific need, it brings me directly to the objects near my location. When I enter the Google browser, it displays ads and advertisements related to my interests without me explicitly stating them to the browser. That’s AI for me.” [R1]

Nevertheless, the overall theme here is that they have little knowledge about what AI is and hold a hugely positive impression of AI without acknowledging many negativities or side effects. To promote successful AI adoption, there is a crucial need to gain a deeper understanding of what AI entails, as well as to establish a shared organizational understanding of AI’s purpose and its connected aims and ambitions. AI awareness guarantees that employees possess sufficient comprehension and anticipation concerning AI (Jöhnk et al., 2021). Further, to our knowledge, AI awareness has not been empirically tested in an organizational adoption study. Based on our qualitative data findings, we contend that addressing the significance of AI awareness can better prepare and equip organizations to successfully integrate AI technologies.
and fully leverage their potential benefits for their employees. Therefore, we propose the following:

**H8: AI awareness will positively influence the intention to adopt AI.**

5.3 Environmental Higher Authority Support

Government support embodies the government's proactive stance in fostering and endorsing emerging technologies, complemented by establishing pertinent standards and policies that act as catalysts in incentivizing the technology adoption process (Zhu & Kraemer, 2005). Within the framework of influencing the adoption of innovative technologies, government support emerges as a prominent determinant (Alsheibani et al., 2020; Bose & Luo, 2011).

Our findings revealed that SAB's concerted efforts in embracing AI were galvanized by the government's heightened focus on rapid technological advancement to realize Saudi Arabia's 2030 vision, which included the establishment of The Saudi Data and AI Authority (SDAIA). In our interviews, participants construed these initiatives as motivational forces propelling them towards AI adoption and shaping the potential contours of the future, with only a single participant expressing a different sentiment, as demonstrated by the following quote:

*As a prevailing trend, Saudi Arabia's leadership has established an artificial intelligence authority [SDAIA] and provided robust support to bolster its functions, concurrently granting it amplified authority. This stance holds significant implications and serves as a clear indication of the kingdom's relentless direction toward adopting AI. The*
unwavering state support for the transition to artificial intelligence is notably manifest in various innovative initiatives, including those evident within NEOM and other ongoing projects. [R8]

In summary, our findings suggest that Higher Authority Support can positively influence the intention to adopt AI among auditors at the SAB. Therefore, we propose the following:

**H9: Higher Authority Support will positively influence the intention to adopt AI.**

Auditees Support

Partner support encompasses the aid, collaboration, and resources extended by external individuals, organizations, or entities sharing a common objective for success. In the context of adopting AI within organizations, the research underscores that partner support can encompass more than just financial backing; it can encompass knowledge sharing, thereby amplifying employees' competence in embracing novel technologies (Chatterjee et al., 2021). Considering the scope of SAB’s audit subjects, encompassing ministries, government entities, private enterprises, and public corporations or bodies linked to the State's financial contributions or profit guarantees, their preparedness and cooperation in the transition are paramount. In our study, we term this dynamic "Auditees support." It refers to the extent to which the entities being audited are equipped with systems and personnel to facilitate the required auditing procedures (Zhu et al., 2006). Sometimes termed "Partner readiness," this factor holds significant importance in fostering the adoption of technological innovations on a broader scale (Zhu et al., 2006).
Our findings substantiate this notion. Interviewees have recounted instances of significant delays caused by auditees returning physical documents instead of utilizing the established electronic channels, as demonstrated by the following quote:

*I enforce the requirement for them to respond via the GovAudit system. In the case of some entities, they insist on sending the documents physically, and if I receive paperwork, I tend to reject it, accepting only automated submissions through the GovAudit system.* [R8]

This is compounded by the need for continuous training from SAB to acquaint auditees with the usage of the existing "GovAudit" system for submitting necessary documents, as demonstrated by the following quote:

“*Some government agencies, despite the Bureau's efforts to provide them with courses, still exhibit limited comprehension of the system, resulting in a sluggish pace of improvement. This prevailing situation indicates that these agencies often struggle to navigate the GovAudit system effectively, reflecting a sense of being disoriented. The challenge lies in the fact that until direct interaction takes place, these agencies seem to grapple with the intricacies of the system.* [R5]”

The frequent rotation of auditees' personnel with limited backgrounds on GovAudit, introduces significant barriers to effective system utilization. As new employees continuously join and others depart the organizations being audited, SAB faces ongoing challenges in ensuring that personnel are well-versed in utilizing GovAudit tools and systems. This perpetual need for training diverts resources and time away from core tasks and hampers the establishment of a
cohesive user base proficient in system functionalities. Consequently, the system's potential to enhance efficiency and collaboration is constrained, as demonstrated by the following quote:

_Similarly, the frequent change of system users within the various over nine hundred and fifty main and subsidiary entities being audited is challenging. Managing such a large number of users demands considerable effort and resources to effectively monitor and maintain their access and interactions…... If an employee [contact point] changes, we have to start from scratch and begin again [in teaching them how to use GovAudit]. [R1]_

We posit that Auditees' support not only affects the correlation between Task-technology fit but also directly impacts the intent to adopt AI tools, as found from our qualitative insights. The extent to which auditees provide requisite support will either facilitate or impede SAB's AI adoption endeavors. Therefore, Auditees support operates as a crucial intermediary, enhancing or hindering the alignment between task demands and the capabilities offered by AI technology. As organizations like SAB navigate the multifaceted landscape of AI adoption, recognizing this moderating link can guide strategic efforts toward a more seamless and successful incorporation of AI tools. Therefore, we propose the following:

_H10: Auditees support moderates the relationship between Task-Technology Fit and the Intention to adopt AI Tools._

5.4 TTF

Audit Task Characteristics

The term "task" denotes the specific actions undertaken by individuals to transform input into output, while "task characteristics" encompass the distinctive attributes of tasks that prompt
individuals to primarily depend on information technology (IT) solutions (Goodhue & Thompson, 1995; Howard & Rose, 2019). Notably, auditors extensively rely on IT tools to execute their daily operations, a practice particularly evident within the SAB context, where the GovAudit system is integral to their auditing activities. This system is especially vital given the extensive interactions with over 950 auditees, spanning both private and public entities. Auditors' responsibilities encompass a range of tasks, including reviewing financial statements, validating accuracy and regulatory compliance, identifying discrepancies, evaluating internal controls, and offering recommendations to enhance financial reporting and the responsible use of public funds.

The significance of auditing tasks lies in their role in upholding transparency, precision, and ethical conduct in financial operations and reporting. Consequently, we posit that the characteristics of these auditing tasks are pivotal in determining the compatibility between tasks and the technological tools employed, specifically AI. As AI integration gains traction in auditing, aligning AI capabilities with the unique characteristics of auditing tasks becomes instrumental in ensuring effective and efficient technology utilization. Therefore, we propose the following:

**H11: Audit Task Characteristics Positively Affect the Task Technology Fit.**

Task Technology fit

Task-Technology Fit (TTF) refers to the level of technical assistance that the information system (IS) provides to individuals in their execution of various tasks (Pillai & Sivathanu, 2020). The central focus of this concept lies in the harmonization between the technological capabilities of the IS and the specific demands of an individual's task portfolio, ensuring smooth task performance and optimal utilization of the technology. TTF is underscored by the principle that
technology becomes truly effective when it enhances individual performance to a degree that aligns seamlessly with their tasks' specific prerequisites (Pillai & Sivathanu, 2020). This alignment is pivotal in influencing an individual's choice to adopt technology for diverse task executions within their professional responsibilities (Goodhue & Thompson, 1995).

Notably, TTF has been identified as a predictive factor for the practical usage of AI in Human Resource Management systems (Pillai & Sivathanu, 2020). Our qualitative analysis substantiates this notion, as our interviewees consistently underscored the significance of AI and the anticipated impact it could have upon adoption. Therefore, we assert that achieving alignment between TTF and AI technology is imperative for the successful adoption of AI by SAB auditors. Any incompatibility between task requirements and AI technology may hinder adoption, thereby emphasizing the importance of this alignment to facilitate a smooth transition.

**H12: TTF positively affects the intention to adopt AI.**

5.5 Control Variables

It is crucial to evaluate the influence of control variables on the dependent variable to mitigate potential confounding effects unrelated to the hypothesized relationships. This dissertation’s control variables included gender, education level, job role category, age group category, and experience level category. Through a post-hoc analysis, these control variables were integrated as independent variables alongside other latent variables using SmartPLS (Will be further discussed in Chapter 6). This approach enabled the examination of path coefficients and the significance of their values. Interestingly, the relationships between the independent and dependent variables remained statistically significant even after incorporating the
aforementioned control variables. This underscores the robustness of the observed relationships and reinforces the validity of the study findings.

CHAPTER 6: PHASE II – Quantitative Component of the Study

In this chapter, we discuss Phase II of our mixed-method study. First, we give an overview of the sample used. Second, we discuss the measures used for our study. Third, we present the analysis of our survey responses. Fourth, we examine our data analysis and corresponding results. Finally, we present the outcomes related to RQ2, concluding this chapter with a summary of Phase II within our mixed-method study.

6.1 Sample

Our survey's target sample comprised approximately 900 SAB auditors actively utilizing the GovAudit system daily. This group of auditors represents those directly affected by the proposed adoption of AI tools. Notably, participants engaged in the qualitative portion will be excluded from this study. After data screening and cleaning, the final sample is 491, which will be discussed further in section 6.3.2.

Our sampling methodology aligns with non-probability "purposive sampling" (Venkatesh et al., 2016), a deliberate selection process based on specific characteristics, expertise, or attributes relevant to the study's objectives. Given the organizational context of a government entity, participant communication, and selection will be facilitated by the government organization itself. However, it is imperative to note that all participants must provide informed consent by signing and submitting a consent form before engaging in the survey (Appendix G).
6.2 Measures

In evaluating the Intention to adopt, we employed an adapted three-item scale from existing literature (Alsaad et al., 2019; Ke et al., 2009; Son & Benbasat, 2007). TTF was assessed using a four-item scale adapted from various papers (Daradkeh, 2019; Hsiao, 2017; T. C.-K. Huang et al., 2013; Jarupathirun, 2007), while Auditing Task Characteristics were measured with a five-item scale adapted from Dhiman & Jamwal (2022).

Within the Technological Constructs, AI Complexity was quantified through a three-item scale adapted from Oliveira et al. (2014). Similarly, Relative Advantage was assessed with a five-item scale from the same source, and Perceived Scalability was measured using a four-item scale (C. Sharma et al., 2023). On the other hand, security was assessed with a five-item scale (Benlian et al., 2011).

Transitioning to Organizational Constructs, AI Awareness utilized a three-item scale adapted from Wang et al. (2022), while AI Strategic Alignment employed an adapted three-item scale (Horani et al., 2023; Liang et al., 2007; Preston & Karahanna, 2009). Organizational Readiness was measured using a four-item scale (Chatterjee et al., 2021; Iacovou et al., 1995; Saad et al., 2022), and Leadership Support was also assessed through a four-item scale (Gangwar et al., 2015).

Concluding with Organizational Constructs, Auditees' Support was gauged using a three-item scale adapted from Chatterjee et al. (2021), and Higher Authority Support was measured using a three-item scale (Chen et al., 2023; Zhu et al., 2006). For all our constructs in the survey, we are using a 5-point Likert scale. The measurement of constructs is presented in Table 5.
<table>
<thead>
<tr>
<th>Construct</th>
<th>Indicator Code</th>
<th>Indicators modified</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auditees Support</td>
<td>AS1</td>
<td>I believe Auditees will assist in the migration process from an existing legacy system to an AI based auditing system.</td>
<td>Adapted from (Chatterjee et al., 2021)</td>
</tr>
<tr>
<td></td>
<td>AS2</td>
<td>I believe Auditees will collaborate in the migration process from an existing legacy system to an AI based auditing system.</td>
<td></td>
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<tr>
<td></td>
<td>AS3</td>
<td>In general Auditees will provide the resources necessary for the successful migration process from an existing legacy system to an AI based auditing system.</td>
<td></td>
</tr>
<tr>
<td>Higher Authority</td>
<td>HS1</td>
<td>The government’s laws support AI technology adoption.</td>
<td>Adapted from (Chen et al., 2023; Zhu et al., 2006)</td>
</tr>
<tr>
<td>Support</td>
<td>HS2</td>
<td>The government provides incentives for AI technology adoption.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>HS3</td>
<td>The government implements AI strategies.</td>
<td></td>
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<tr>
<td>AI Awareness</td>
<td>AA1</td>
<td>I can distinguish between AI devices and non-AI devices.</td>
<td>Adapted from (Wang et al., 2022)</td>
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<tr>
<td></td>
<td>AA2</td>
<td>I do know how AI technology can help me.</td>
<td></td>
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<tr>
<td></td>
<td>AA3</td>
<td>I can identify the AI technology employed in the applications and products I use.</td>
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<tr>
<td>AI strategic</td>
<td>SA1</td>
<td>Our business strategy and AI strategy are closely aligned.</td>
<td>Adapted from (Horani et al., 2023; Liang et al., 2007, 2017; Preston &amp; Karahanna, 2009)</td>
</tr>
<tr>
<td>alignment</td>
<td>SA2</td>
<td>Our AI plan supports the business strategies.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SA3</td>
<td>The AI strategy is congruent with the corporate business strategy in our organization.</td>
<td></td>
</tr>
<tr>
<td>Organizational</td>
<td>OR1</td>
<td>Our organization is financially ready to use AI Auditing tools.</td>
<td>Adapted from (Saad et al., 2022; Chatterjee et al., 2021; Iacovou et al., 1995)</td>
</tr>
<tr>
<td>Readiness</td>
<td>OR2</td>
<td>Our organization has enough technological resources to use AI Auditing tools.</td>
<td></td>
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<td></td>
<td>OR3</td>
<td>In our organization, employees have adequate knowledge to use AI Auditing tools.</td>
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<td></td>
<td>OR4</td>
<td>Our organization provides various ways (virtual, in person, etc.) of training in AI for auditing.</td>
<td></td>
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<tr>
<td>Leadership</td>
<td>LS1</td>
<td>Our top management exhibits a culture of enterprise-wide information sharing regarding AI.</td>
<td>Adapted from (Gangwar et al. 2015)</td>
</tr>
<tr>
<td>Support</td>
<td>LS2</td>
<td>The organization’s top management provides strong leadership and engages in the process when it comes to AI tools within the organization.</td>
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<td></td>
<td>LS3</td>
<td>Our organization’s top management is likely to consider the adoption of AI tools as strategically important.</td>
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<td></td>
<td>LS4</td>
<td>Our organization’s top management is willing to take risks involved in the adoption of AI tools.</td>
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</tr>
<tr>
<td>AI Complexity</td>
<td>CX1</td>
<td>Adopting AI tools within our organization will demand considerable mental effort.</td>
<td>Adapted from (Oliveira et al., 2014)</td>
</tr>
<tr>
<td></td>
<td>CX2</td>
<td>Incorporating AI tools into our auditing processes and operations will be challenging.</td>
<td></td>
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<tr>
<td></td>
<td>CX3</td>
<td>Acquiring the skills required for using AI tools within our organization will be complex.</td>
<td></td>
</tr>
<tr>
<td>Perceived</td>
<td>SC1</td>
<td>AI tools’ capacity can be increased to handle increasing auditing workloads through 24x7 utilization.</td>
<td>Adapted from (Sharma et al. 2023)</td>
</tr>
<tr>
<td>Scalability</td>
<td>SC2</td>
<td>AI tools’ capacity can be increased to handle increasing auditing workloads by quickly adjusting their computational resources.</td>
<td></td>
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<td></td>
<td>SC3</td>
<td>AI tools can be easily extended to handle additional auditing task without compromising performance.</td>
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<td></td>
<td>SC4</td>
<td>An AI tool can be assigned to multiple auditing tasks at the same time.</td>
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<tr>
<td>Relative Advantage</td>
<td>RA1</td>
<td>AI tools allow you to manage auditing tasks in an efficient way.</td>
<td>Adapted from (Oliveira et al., 2014)</td>
</tr>
<tr>
<td></td>
<td>RA2</td>
<td>The use of AI tools improves the quality and accuracy of auditing tasks.</td>
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<td></td>
<td>RA3</td>
<td>Using AI tools allows you to perform specific auditing tasks more quickly and effectively.</td>
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<tr>
<td></td>
<td>RA4</td>
<td>The use of AI tools offers new opportunities for enhancing auditing processes.</td>
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<tr>
<td></td>
<td>RA5</td>
<td>Using AI tools allows you to increase efficiency and productivity in auditing tasks.</td>
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<tr>
<td>Security</td>
<td>SE1</td>
<td>My organization has adequate data backup and recovery.</td>
<td>Adapted from (Benlian et al., 2011)</td>
</tr>
<tr>
<td></td>
<td>SE2</td>
<td>My organization conducts regular security audit</td>
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<tr>
<td>SE3</td>
<td>My organization has adequate data confidentiality measures</td>
<td></td>
<td></td>
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<tr>
<td>SE4</td>
<td>My organization has adequate data encryption measures</td>
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<tr>
<td>SE5</td>
<td>My organization provides a secure physical environment (i.e., secure data center)</td>
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<tr>
<td>IA1</td>
<td>Our organization intends to adopt AI tools to enhance our auditing operations in the near future.</td>
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<tr>
<td>IA2</td>
<td>It is likely that our organization will take some steps to adopt AI tools in the near future.</td>
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<tr>
<td>IA3</td>
<td>We believe it is worthwhile for our organization to adopt AI tools in the near future.</td>
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<tr>
<td>TC1</td>
<td>I require to gather more information while performing auditing tasks.</td>
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<tr>
<td>TC2</td>
<td>My auditing tasks require me to review and analyze financial records and reports.</td>
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<tr>
<td>TC3</td>
<td>My auditing tasks also require me to communicate with relevant stakeholders and teams to resolve any audit-related issues.</td>
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<tr>
<td>TC4</td>
<td>During auditing tasks, I need to explore different audit approaches and methodologies to ensure accuracy and compliance.</td>
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<tr>
<td>TC5</td>
<td>My auditing tasks require me to stay updated and informed about the latest auditing standards and regulations.</td>
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<tr>
<td>TF1</td>
<td>I think the functionalities of AI tools are very adequate for our organization's auditing tasks.</td>
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<tr>
<td>TF2</td>
<td>I think the functionalities of AI tools are very appropriate for our organization's auditing tasks.</td>
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<td></td>
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<tr>
<td>TF3</td>
<td>I think the functionalities of AI tools are very useful for our organization's auditing tasks.</td>
<td></td>
<td></td>
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<tr>
<td>TF4</td>
<td>In general, I think the functionalities of AI tools are the best fit for our organization's daily auditing tasks.</td>
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### 6.3 Survey Response Analysis

The survey link was sent to the SAB management team, who distributed it to the auditors. The response collection period spanned the first two weeks of May 2024. Data was collected through the online platform "QuestionPro," then downloaded and analyzed using Excel and SmartPLS. The analysis focused on determining the reliability and validity of the data and testing the hypotheses.

**Response Rate and Data Screening**

A total of 943 responses were collected, with 703 completed responses, resulting in a 74.55% completion rate. Completed responses are those where participants started and finished the survey. On average, respondents took 11 minutes to complete the survey. Our multilingual survey offered participants the option to choose their preferred language at the start. Most
respondents completed the survey in Arabic (689), while a small number opted for English (14). This multilingual approach ensured inclusivity and accuracy, catering to the respondents' language preferences.

For our data screening, we conducted two steps to ensure the quality of the responses. First, we included two attention-check questions in the survey: one placed early and another later in the survey. These questions instructed respondents to choose “Strongly Agree” or “Strongly Disagree.” Out of the 703 respondents who completed the survey, 504 passed these attention checks. Second, from those who passed the attention checks, we selected respondents who provided complete answers to every question in the survey. This reduced the number from 504 to 491 participants. We allowed respondents to skip questions if they chose, but only those who answered all questions were included in the final analysis.

To calculate the necessary sample size for this study, we employed two methods to ensure we had an adequate minimum sample for our testing. In the first method, we used the G*Power 3.1 software proposed by Faul et al. (2007). The settings included an effect size of 0.3, an alpha level of 0.05, 10 predictors, and a power level of 95% (Gefen et al., 2011). Based on this analysis, the minimum required sample size was 132.

For the second method, we utilized the A-priori Sample Size Calculator for Structural Equation Models (Cohen, 2013; Soper, 2020). Here, the settings were an effect size of 0.3, an alpha level of 0.05, 13 latent variables, 47 observed variables, and a desired statistical power level of 95%. This analysis recommended a minimum sample size of 288.

Additionally, according to the suggestions of Hair et al. and Cohen et al., the sample size should be at least two to three times the calculated size using G*Power software. Hair et al.
(2010) also state that a sample size of 400 or more is adequate for ensuring statistical power and robustness in structural equation modeling. Our actual sample size of 491 is well above these recommended thresholds, ensuring robustness in our testing. This final sample size is sufficient for validating our research model identified in Phase I of our mixed-method study.

Descriptive Statistics of Respondents

The primary criterion for our respondents is their regular use of the GovAudit workflow system to conduct auditing tasks within the system. This criterion applies to three types of respondents: Auditors, Department Managers, and General Managers. Auditors constitute 85% of our respondents, making them the majority group in this study, as anticipated, due to their more significant representation among system users. Additionally, 84% of the respondents are male, which aligns with expectations considering recent efforts by SAB to increase female hiring and salaries. Among the 78 female respondents, all are Auditors, possess at least a bachelor's degree, and fall within the under-40 age group.

Regarding educational qualifications, approximately 80.4% of all respondents hold a bachelor's degree, while 16.7% have a master's degree or higher. Regarding age distribution, the respondents are diversified, with 47% falling within the 30-40 age range, while the under-30 and 41-50 age groups each represent approximately 44% of the remaining respondents. Experience levels are evenly distributed among the respondents, with 38.9% having more than 12 years of experience, 20% having 8-12 years, 22.2% having 4-7 years, and 14.3% having 1-3 years of experience. Table 6 provides the demographic information of the respondents.

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<th>Demographics</th>
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Table 6. Respondents’ demographic information
Data Normality

Ensuring the data's normality is essential before applying specific multivariate data analysis techniques, such as regression analysis and structural equation modeling (SEM). If the data do not meet the normality assumption, alternative methods, such as PLS-SEM, must be used (Henseler et al., 2009).

The normality of the data was assessed using the Shapiro-Wilk test. Results indicated significant values of 0.00 for all variables, suggesting non-normal data distribution. This violation of the data's normality assumption reinforces the appropriateness of employing PLS-
SEM for analysis. In such cases of non-normal data, PLS-SEM offers robustness and flexibility in handling complex relationships and is well-suited for analyzing data without strict distributional assumptions. Furthermore, using PLS-SEM allows for accurate estimation of model parameters and provides reliable insights even in the presence of non-normal data. Therefore, the decision to utilize PLS-SEM in this study is well-justified, ensuring valid and reliable analysis outcomes despite the non-normality of the data.

6.4 Data Analysis and Results

This section presents the statistical technique used and the results of analyses conducted. First, we describe the statistical technique and software used. Second, the validity and reliability of the measurement model is assessed. Third, the structural model is analyzed to test the hypotheses. This results section follows the widely accepted reporting style of PLS analysis as suggested by previous studies (Chin, 2009; Vinzi et al., 2010). Additionally, we present the outcomes of RQ2, concluding this section with a summary of Phase II within our mixed-method study.

6.4.1 Brief Introduction to Statistical Technique Used (PLS)

This study used Partial Least Squares (PLS) as the primary statistical technique to analyze the collected data. PLS is a robust multivariate analysis method suited for complex models and varying sample sizes, including small to medium samples (Sarstedt et al., 2021). It is highly effective when the research involves multiple dependent and independent variables with potential collinearity. By integrating principal component analysis and multiple regression, PLS allows for the simultaneous examination of relationships among observed variables and latent
constructs. This method is adept at predicting outcomes and provides valuable insights into the structural model, making it an ideal choice for the present study’s analytical framework.

Although PLS is often highlighted for its utility in small to medium sample sizes, it is equally suitable for large samples (Akter et al., 2017; Hair et al., 2019). PLS can handle large datasets effectively due to its computational efficiency and scalability. The method’s ability to manage large numbers of predictors without overfitting makes it advantageous for extensive datasets. Furthermore, with larger samples, PLS can provide more stable and generalizable estimates, enhancing the robustness of the model's predictive power and the reliability of the derived latent constructs. The technique's versatility and robustness across varying sample sizes are well-documented in the literature. For instance, Hair et al. (2017) emphasize that PLS-SEM is appropriate for large samples as it can accommodate the complexity and scale of extensive data structures without sacrificing accuracy or interpretability.

Additionally, PLS-SEM use in this study is further justified by its ability to handle non-normal data distributions, often encountered in social sciences and marketing research. PLS does not assume the normality of data, making it a robust choice when normal distribution cannot be guaranteed (Henseler et al., 2009). This characteristic, combined with its predictive capability and flexibility in model specification, underscores the suitability of PLS for the current research. By employing PLS-SEM, the study is equipped to deliver nuanced and reliable insights, enhancing the overall validity and impact of the findings.

This dissertation utilizes established analytic criteria, employing a partial least squares structural equation modeling (PLS-SEM) approach to evaluate the research model. Several considerations guided the decision to use PLS-SEM:
1. The primary focus of this dissertation is not on measuring model invariance but on predicting factors related to the intention to adopt AI tools in auditing. Therefore, using latent variable scores is crucial for examining the underlying relationships between latent variables (Sosik et al., 2009).

2. According to Henseler et al. (2009), PLS suits large, complex models with many latent variables. This dissertation involves a relatively complex research model with many latent variables, making PLS-SEM an appropriate choice.

3. This dissertation aims to explore relationships based on qualitative findings from Phase I and prior theoretical knowledge. PLS-SEM can estimate correlations between residuals and assess their effects on the model, which aligns with the objectives of this study.

Using SmartPLS Software for PLS Analysis

For the Partial Least Squares (PLS) analysis, the SmartPLS software (Version 4.1.0.2.) was utilized due to its user-friendly interface, advanced capabilities, and widespread acceptance in academic research. SmartPLS is designed explicitly for Structural Equation Modeling (SEM) using the PLS approach, providing a comprehensive set of tools for model estimation, validation, and hypothesis testing. Its graphical user interface simplifies the model construction process, allowing researchers to visually represent complex relationships between variables and easily modify model specifications as needed (Henseler et al., 2015).

SmartPLS offers several key features that enhance the analysis process. First, it supports handling large datasets and complex models with numerous indicators and constructs, making it ideal for research involving extensive data and intricate relationships (Hair et al., 2017). The
software also provides robust algorithms for model estimation, including the PLS algorithm, bootstrapping, and blindfolding procedures, which ensure accurate and reliable results (Henseler et al., 2015). Additionally, SmartPLS includes advanced functionalities for assessing model fit, such as the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI), which help in evaluating the goodness-of-fit for the structural model (Hair et al., 2017; Sarstedt et al., 2021).

Moreover, SmartPLS facilitates the assessment of both the measurement and structural models (Ringle, 2015; Ringle et al., 2012; K. K.-K. Wong, 2013). In the measurement model, the software allows for the evaluation of indicator reliability, internal consistency reliability (e.g., Cronbach’s alpha, composite reliability), convergent validity (e.g., Average Variance Extracted, AVE), and discriminant validity (e.g., Fornell-Larcker criterion, HTMT ratio) (Henseler et al., 2015). For the structural model, SmartPLS provides insights into path coefficients, R-squared values, effect sizes (f-squared), and predictive relevance (Q-squared), thereby enabling a thorough examination of the hypothesized relationships and the model's explanatory power (Hair et al., 2017).

One of the notable strengths of SmartPLS is its ability to perform multigroup analysis (MGA) and easily handle moderation and mediation effects. This is particularly useful for exploring whether the relationships between variables differ across subgroups or if certain variables influence the strength or direction of the relationships (Henseler et al., 2015). The software’s bootstrapping technique, which generates standard errors and confidence intervals for significance testing, further enhances the robustness of the findings by providing empirical validation for the paths in the model (Hair et al., 2017).
In conclusion, this study chose SmartPLS for conducting the PLS analysis because of its advanced analytical capabilities, ease of use, and comprehensive support for evaluating complex models. By leveraging SmartPLS, this research benefits from a rigorous and methodologically sound approach to SEM, ensuring that the derived insights are credible and actionable.
6.4.2 Measurement Model Assessment

The quality of the constructs in this study is evaluated by assessing the measurement model. The initial phase of PLS-SEM analysis entails evaluating the measurement model, which encompasses reflectively measured constructs, composite reliability, indicator reliability, convergent validity, and discriminant validity (Hair et al., 2011). This evaluation begins with examining factor loadings, followed by establishing construct reliability and construct validity (Gefen & Straub, 2005).

**Factor Loading**

Factor loading measures the degree to which each item in the correlation matrix correlates with a given principal component. Factor loadings can range from -1.0 to +1.0, with higher absolute values indicating a stronger correlation between the item and the underlying factor (Pett et al., 2003). Typically, items with outer loadings ranging from 0.40 to 0.70 are considered for removal only if their exclusion results in an enhancement of composite reliability or average variance extracted (AVE) surpassing the recommended threshold (Hair Joe F et al., 2016). In this study, all items had factor loadings above the recommended threshold of 0.50 (Hair Joe F et al., 2016), except for CX1 and TC5. CX1 was eliminated due to a low factor loading (<0.500) and TC5 due to its impact on AVE, even though the loading was above the 0.5 threshold (Gefen & Straub, 2005). The factor loadings are detailed in Table 9.
Table 7. Factor Loadings

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Indicator Multicollinearity

The Variance Inflation Factor (VIF) statistic assesses multicollinearity among indicators (Fornell & Bookstein, 1982). According to Hair et al. (2016), multicollinearity is not a serious issue if the VIF value is below 5. Table 10 shows the outer model VIF values for the indicators in this study, indicating that all values are below the recommended threshold, thus confirming that multicollinearity is not a concern.

Table 8. Multicollinearity Statistics (VIF) for indicators

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Reliability Analysis

Trochim and Donnelly (2001) define reliability as the stability and consistency of a measuring instrument, emphasizing that its essence lies in repeatability—yielding the same
results when administered multiple times. The two most common methods for establishing reliability are Cronbach's Alpha and Composite Reliability (CR). Table 11 presents the results for both metrics. Cronbach's Alpha values ranged from 0.701 to 0.938, while Composite Reliability statistics ranged from 0.811 to 0.953. Both indicators exceed the required threshold of 0.70 (Hair et al., 2011). The rho_A value, positioned between Cronbach’s alpha and composite reliability, also surpassed 0.7, indicating robust reliability (Henseler et al., 2016; Sarstedt et al., 2021). Thus confirming construct reliability.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Cronbach's alpha</th>
<th>Composite reliability (rho_a)</th>
<th>Composite reliability (rho_c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Awareness</td>
<td>0.814</td>
<td>0.849</td>
<td>0.888</td>
</tr>
<tr>
<td>AI Complexity</td>
<td>0.807</td>
<td>0.920</td>
<td>0.908</td>
</tr>
<tr>
<td>AI Strategic Alignment</td>
<td>0.870</td>
<td>0.873</td>
<td>0.920</td>
</tr>
<tr>
<td>Auditees Support</td>
<td>0.850</td>
<td>0.851</td>
<td>0.909</td>
</tr>
<tr>
<td>Higher Authority Support</td>
<td>0.898</td>
<td>0.901</td>
<td>0.936</td>
</tr>
<tr>
<td>Intention to Adopt</td>
<td>0.828</td>
<td>0.832</td>
<td>0.897</td>
</tr>
<tr>
<td>Leadership Support</td>
<td>0.895</td>
<td>0.899</td>
<td>0.927</td>
</tr>
<tr>
<td>Organizational Readiness</td>
<td>0.834</td>
<td>0.845</td>
<td>0.888</td>
</tr>
<tr>
<td>Perceived Scalability</td>
<td>0.813</td>
<td>0.821</td>
<td>0.876</td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>0.938</td>
<td>0.938</td>
<td>0.953</td>
</tr>
<tr>
<td>Security</td>
<td>0.909</td>
<td>0.919</td>
<td>0.932</td>
</tr>
<tr>
<td>Task Characteristics</td>
<td>0.701</td>
<td>0.715</td>
<td>0.811</td>
</tr>
<tr>
<td>Task Technology Fit</td>
<td>0.931</td>
<td>0.933</td>
<td>0.951</td>
</tr>
</tbody>
</table>

**Construct Validity**

Construct validity is established in PLS-SEM analysis by demonstrating convergent and discriminant validity. Convergent validity ensures that indicators of a construct are highly correlated and accurately measure the same concept. Discriminant validity verifies that constructs are distinct and indicators do not overlap significantly. Both forms of validity are crucial for confirming the accuracy and integrity of the measurement model.
Convergent Validity is the extent to which different attempts to measure the same concept agree. Essentially, if two or more measures of the same concept are valid, they should correlate highly (Bagozzi et al., 1991). Convergent validity is established when the Average Variance Extracted (AVE) value is greater than or equal to the recommended threshold of 0.50, indicating that the items collectively measure the underlying construct (Fornell & Larcker, 1981). In this study, the AVE values for all constructs met this criterion, and CR values for all constructs exceeded 0.70 (As established in Table 12). Thus, convergent validity is not a concern. Table 12 presents the AVE values for each construct, confirming that convergent validity is satisfactorily established for all constructs.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Average variance extracted (AVE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Awareness</td>
<td>0.726</td>
</tr>
<tr>
<td>AI Complexity</td>
<td>0.832</td>
</tr>
<tr>
<td>AI Strategic Alignment</td>
<td>0.793</td>
</tr>
<tr>
<td>Auditees Support</td>
<td>0.769</td>
</tr>
<tr>
<td>Higher Authority Support</td>
<td>0.831</td>
</tr>
<tr>
<td>Intention to Adopt</td>
<td>0.745</td>
</tr>
<tr>
<td>Leadership Support</td>
<td>0.760</td>
</tr>
<tr>
<td>Organizational Readiness</td>
<td>0.666</td>
</tr>
<tr>
<td>Perceived Scalability</td>
<td>0.639</td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>0.802</td>
</tr>
<tr>
<td>Security</td>
<td>0.735</td>
</tr>
<tr>
<td>Task Characteristics</td>
<td>0.519</td>
</tr>
<tr>
<td>Task Technology Fit</td>
<td>0.829</td>
</tr>
</tbody>
</table>

"Discriminant Validity is the degree to which measures of different concepts are distinct. The notion is that if two or more concepts are unique, then valid measures of each should not correlate too highly" (Bagozzi et al., 1991). This distinctiveness is crucial for maintaining the
measured constructs' integrity and specificity. Discriminant validity is assessed using the *Fornell and Larcker Criterion* and *Heterotrait-Monotrait Ratio (HTMT)*.

According to Fornell and Larcker’s (1981) *criterion*, discriminant validity is confirmed when the square root of the AVE for a construct exceeds its correlations with all other constructs. In this study, the square root of AVE (presented in bold and italics) for each construct was greater than its correlations with other constructs, as established in Table 13. This result provides strong evidence supporting the establishment of discriminant validity, ensuring that each construct is unique and distinct from the others.

**Table 11. Discriminant Validity - Fornell & Larcker Criterion**

<table>
<thead>
<tr>
<th></th>
<th>AA</th>
<th>CX</th>
<th>SA</th>
<th>AS</th>
<th>HS</th>
<th>IA</th>
<th>LS</th>
<th>OR</th>
<th>SC</th>
<th>RA</th>
<th>SE</th>
<th>TC</th>
<th>TF</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Awareness</td>
<td>0.852</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI Complexity</td>
<td>-0.040</td>
<td>0.912</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI Strategic Alignment</td>
<td>0.474</td>
<td>-0.163</td>
<td>0.891</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Auditees Support</td>
<td>0.253</td>
<td>-0.168</td>
<td>0.441</td>
<td>0.877</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher Authority Support</td>
<td>0.312</td>
<td>-0.119</td>
<td>0.457</td>
<td>0.309</td>
<td>0.911</td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Intention to Adopt</td>
<td>0.269</td>
<td>-0.206</td>
<td>0.494</td>
<td>0.350</td>
<td>0.442</td>
<td>0.863</td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Leadership Support</td>
<td>0.397</td>
<td>-0.203</td>
<td>0.649</td>
<td>0.419</td>
<td>0.414</td>
<td>0.451</td>
<td>0.872</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Organizational Readiness</td>
<td>0.417</td>
<td>-0.201</td>
<td>0.665</td>
<td>0.452</td>
<td>0.346</td>
<td>0.415</td>
<td>0.717</td>
<td>0.816</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Perceived Scalability</td>
<td>0.397</td>
<td>-0.031</td>
<td>0.439</td>
<td>0.306</td>
<td>0.316</td>
<td>0.484</td>
<td>0.390</td>
<td>0.369</td>
<td>0.799</td>
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<td></td>
<td></td>
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<tr>
<td>Relative Advantage</td>
<td>0.297</td>
<td>-0.224</td>
<td>0.493</td>
<td>0.352</td>
<td>0.408</td>
<td>0.603</td>
<td>0.365</td>
<td>0.360</td>
<td>0.564</td>
<td>0.895</td>
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</tr>
<tr>
<td>Security</td>
<td>0.271</td>
<td>-0.127</td>
<td>0.356</td>
<td>0.288</td>
<td>0.240</td>
<td>0.288</td>
<td>0.485</td>
<td>0.449</td>
<td>0.271</td>
<td>0.211</td>
<td>0.857</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task Characteristics</td>
<td>0.252</td>
<td>0.077</td>
<td>0.195</td>
<td>0.068</td>
<td>0.206</td>
<td>0.186</td>
<td>0.145</td>
<td>0.059</td>
<td>0.240</td>
<td>0.223</td>
<td>0.102</td>
<td>0.720</td>
<td></td>
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<tr>
<td>Task Technology Fit</td>
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<td>-0.188</td>
<td>0.500</td>
<td>0.357</td>
<td>0.404</td>
<td>0.493</td>
<td>0.311</td>
<td>0.333</td>
<td>0.451</td>
<td>0.589</td>
<td>0.135</td>
<td>0.270</td>
<td>0.911</td>
</tr>
</tbody>
</table>

*Note: Bold and Italics represent the square-root of AVE*

HTMT, which relies on estimating correlations between constructs, is a crucial metric for establishing discriminant validity. However, determining a universal threshold for HTMT has been debated in existing literature. Kline (2011) advocates for a conservative threshold of .85 or lower, whereas (Teo et al., 2008) propose a more lenient threshold of .90 or lower. The HTMT
results, as displayed in Table 14, indicate that the HTMT ratio is well below the stipulated threshold of .85 and .90. This finding strengthens the evidence supporting the presence of discriminant validity in the study’s constructs.
Table 12. Discriminant - HTMT

<table>
<thead>
<tr>
<th>AA</th>
<th>CX</th>
<th>SA</th>
<th>AS</th>
<th>HS</th>
<th>IA</th>
<th>LS</th>
<th>OR</th>
<th>SC</th>
<th>RA</th>
<th>SE</th>
<th>TC</th>
<th>TF</th>
<th>AS x TF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>AI Complexity</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>AI Strategic Alignment</td>
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<td>0.18</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auditees Support</td>
<td>9</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Higher Authority Support</td>
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<td>0.18</td>
<td>0.51</td>
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</tr>
<tr>
<td>Intention to Adopt</td>
<td>0.36</td>
<td>0.14</td>
<td>0.51</td>
<td>0.35</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leadership Support</td>
<td>8</td>
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<td>9</td>
<td>4</td>
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<td></td>
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</tr>
<tr>
<td>Organizational Readiness</td>
<td>0.31</td>
<td>0.24</td>
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<td>3</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>0.46</td>
<td>0.23</td>
<td>0.73</td>
<td>0.48</td>
<td>0.46</td>
<td>0.51</td>
<td></td>
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</tr>
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<td>0</td>
<td>1</td>
<td>7</td>
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<td></td>
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</tr>
<tr>
<td>Task Characteristics</td>
<td>0.50</td>
<td>0.24</td>
<td>0.77</td>
<td>0.53</td>
<td>0.39</td>
<td>0.48</td>
<td>0.83</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Task Technology Fit</td>
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<td>1</td>
<td>6</td>
<td>8</td>
<td>7</td>
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<td></td>
</tr>
<tr>
<td>Auditees Support x Task</td>
<td>0.48</td>
<td>0.07</td>
<td>0.51</td>
<td>0.35</td>
<td>0.36</td>
<td>0.58</td>
<td>0.45</td>
<td>0.43</td>
<td></td>
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</tr>
<tr>
<td>Technology Fit</td>
<td>0.32</td>
<td>0.25</td>
<td>0.54</td>
<td>0.39</td>
<td>0.44</td>
<td>0.68</td>
<td>0.39</td>
<td>0.39</td>
<td>0.63</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Common Method Bias (CMB)</td>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Common Method Bias can arise when independent and dependent variables are measured within a single survey using the same response method, such as ordinal scales. This is a frequent issue in research, prompting extensive discussions on identifying,
preventing, and managing common method bias (Burton-Jones, 2009; Jakobsen & Jensen, 2015; Podsakoff et al., 2012, 2024). Common method bias can create false relationships between variables, leading to inflated or distorted findings. Consequently, it can compromise the validity and reliability of research results.

Several attempts were made in this study to minimize the sources of common method bias. First, we followed the recommendations of Podsakoff et al. (Podsakoff et al., 2012, 2024) to minimize sources of common method variance, implementing several procedural remedies: 1) Common scale anchors: Different use of Anchor points were used for items (Strongly Agree-Strongly Disagree, Likely-Not Likely, …). 2) Reducing social desirability: To protect respondent anonymity, the introductory section included statements emphasizing the preservation of anonymity, assuring participants that there are no right or wrong answers. Additionally, respondents were encouraged to answer questions honestly to contribute meaningfully to academic research. 3) Item wording: Avoided using negatively worded items since this may influence the observed relationships between variables.

Second, another assessment was done using the Variance Inflation Factor (VIF) values within the inner model in SmartPLS. In this study, all VIF values were below the 3.33 threshold, indicating that the model is free from common method bias (Kock, 2015). Table 7 shows the results of the VIF inner model.

<table>
<thead>
<tr>
<th></th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Technology Fit -&gt; Intention to Adopt</td>
<td>1.521</td>
</tr>
</tbody>
</table>
Finally, we used a Marker Variable to assess CMB as well. A marker variable is a technique used to detect common method bias by including a specific variable in the research design that indicates potential bias. This variable is intentionally chosen because it is presumed to be theoretically unrelated to the substantive constructs being studied. If the marker variable exhibits significant correlations with other constructs in the model, it may indicate the presence of common method bias. As shown in Table 8, the results show no significant changes in the coefficients, regardless of the inclusion of the marker variable. Thus, it is reasonable to conclude that common method bias is not a significant concern in this study.
Table 14. Marker Variable Analysis - CMB

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model A (Without Marker Variable)</th>
<th>Model B (With Marker Variable)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Original sample (O)</td>
<td>Standard deviation (STDEV)</td>
</tr>
<tr>
<td>AI Awareness -&gt; Intention to Adopt</td>
<td>-0.032</td>
<td>0.043</td>
</tr>
<tr>
<td>AI Complexity -&gt; Task Technology Fit</td>
<td>-0.094</td>
<td>0.036</td>
</tr>
<tr>
<td>AI Strategic Alignment -&gt; Intention to Adopt</td>
<td>0.126</td>
<td>0.058</td>
</tr>
<tr>
<td>Age Category -&gt; Intention to Adopt</td>
<td>-0.059</td>
<td>0.124</td>
</tr>
<tr>
<td>Auditees Support -&gt; Intention to Adopt</td>
<td>0.046</td>
<td>0.044</td>
</tr>
<tr>
<td>Education Level -&gt; Intention to Adopt</td>
<td>-0.076</td>
<td>0.226</td>
</tr>
<tr>
<td>Gender -&gt; Intention to Adopt</td>
<td>-0.255</td>
<td>0.103</td>
</tr>
<tr>
<td>Higher Authority Support -&gt; Intention to Adopt</td>
<td>0.161</td>
<td>0.042</td>
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<tr>
<td>Job Role -&gt; Intention to Adopt</td>
<td>0.198</td>
<td>0.142</td>
</tr>
<tr>
<td>Leadership Support -&gt; Intention to Adopt</td>
<td>0.130</td>
<td>0.069</td>
</tr>
<tr>
<td>Organizational Readiness -&gt; Intention to Adopt</td>
<td>0.045</td>
<td>0.063</td>
</tr>
<tr>
<td>Overall Experience -&gt; Intention to Adopt</td>
<td>-0.097</td>
<td>0.161</td>
</tr>
<tr>
<td>Perceived Scalability -&gt; Task Technology Fit</td>
<td>0.164</td>
<td>0.049</td>
</tr>
<tr>
<td>Relative Advantage -&gt; Task Technology Fit</td>
<td>0.444</td>
<td>0.042</td>
</tr>
<tr>
<td>Security -&gt; Intention to Adopt</td>
<td>0.092</td>
<td>0.046</td>
</tr>
<tr>
<td>Task Characteristics -&gt; Task Technology Fit</td>
<td>0.139</td>
<td>0.038</td>
</tr>
<tr>
<td>Task Technology Fit -&gt; Intention to Adopt</td>
<td>0.272</td>
<td>0.048</td>
</tr>
<tr>
<td>Auditees Support x Task Technology Fit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intention to Adopt</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.040</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.931</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.176</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.037</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.861</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.195</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
6.4.3 Structural Model Assessment

Once the measurement model assessment meets the required standards, the next phase in evaluating PLS-SEM results involves the structural model assessment. This assessment should consider several key criteria: the coefficient of determination ($R^2$), the cross-validated redundancy measure ($Q^2$) derived from blindfolding, and the statistical significance and relevance of the path coefficients. Validating the structural model can help evaluate systematically whether the data supports the hypotheses expressed by the structural model.

An essential criterion for evaluating the structural model is to assess $R^2$ for each endogenous latent variable. $R^2$ quantifies the proportion of explained variance in a latent variable relative to its total variance, providing insight into the strength of the relationship. The $R^2$, also known as in-sample predictive power (Rigdon, 2012), varies between 0 and 1, with higher values indicating more robust explanatory capabilities. Generally, $R^2$ values of 0.67, 0.33, and 0.19 are deemed substantial, moderate, and weak, respectively (Chin, 1998). However, what constitutes acceptable $R^2$ values vary depending on the research context. In specific disciplines, an $R^2$ value as modest as 0.10 may be deemed satisfactory (Hair et al., 2019).

Another vital criterion in assessing the structural model involves examining the path coefficient, which indicates the strength of the relationship between two latent variables. In analyzing this relationship, researchers should carefully consider not only the path coefficients but also their algebraic signs, magnitudes, and significance levels. This comprehensive evaluation ensures a thorough understanding of the relationships between latent variables to establish our hypothesis results.
In this dissertation, we employed a one-tailed bootstrapping method with 10,000 subsamples, utilizing the percentile bootstrap confidence interval approach and maintaining a significance level of 0.05. This rigorous approach ensured robustness in our statistical analysis, allowing for a confident interpretation of the results within the specified significance level.

**Coefficient of Determination ($R^2$)**

$R^2$ signifies the extent of variance in a dependent variable accounted for by the independent variables. Essentially, it reflects the proportion of variability elucidated by the measurement model, with higher values indicating a better explanation of the endogenous latent variable's variance. Therefore, a higher $R^2$ enhances the predictive capacity of the structural model. The results in Table 15 show that the $R^2$ for all our endogenous constructs is over 0.39, which shows moderate model explanatory power (Chin, 1998).

<table>
<thead>
<tr>
<th>Endogenous constructs</th>
<th>R-square</th>
<th>R-square adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intention to Adopt</td>
<td>0.401</td>
<td>0.384</td>
</tr>
<tr>
<td>Task Technology Fit</td>
<td>0.391</td>
<td>0.386</td>
</tr>
</tbody>
</table>

**Hypotheses Testing**

In the structural model, each path links two latent variables, embodying a hypothesis. Path coefficients enable researchers to validate or refute each hypothesis and gain a deeper insight into the intensity of the relationship between dependent and independent variables. Similar to standardized beta coefficients in ordinary least squares regression, these coefficients
provide a numerical understanding of the relationships. Path coefficients’ significance and t-statistics are determined using a bootstrapping technique.

Table 16 provides a comprehensive overview of all proposed relationships' path coefficients, t-statistics, and significance levels. Based on the findings from the path analysis, each hypothesis is either accepted or rejected, contributing to the overall understanding of the structural model.

Table 16. Direct Relationships Results - Structural Model

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path Coefficient</th>
<th>STDEV</th>
<th>T-value</th>
<th>p-value</th>
<th>BI [5-95%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: AI Complexity -&gt; Task Technology Fit</td>
<td>-0.094</td>
<td>0.036</td>
<td>2.64</td>
<td>0.004**</td>
<td>[-0.155; -0.040]</td>
</tr>
<tr>
<td>H2: Perceived Scalability -&gt; Task Technology Fit</td>
<td>0.164</td>
<td>0.049</td>
<td>3.351</td>
<td>0.000***</td>
<td>[0.084; 0.242]</td>
</tr>
<tr>
<td>H3: Relative Advantage -&gt; Task Technology Fit</td>
<td>0.444</td>
<td>0.042</td>
<td>10.522</td>
<td>0.000***</td>
<td>[0.371; 0.510]</td>
</tr>
<tr>
<td>H4: Security -&gt; Intention to Adopt</td>
<td>0.092</td>
<td>0.046</td>
<td>1.995</td>
<td>0.023*</td>
<td>[0.014; 0.166]</td>
</tr>
<tr>
<td>H5: Leadership Support -&gt; Intention to Adopt</td>
<td>0.130</td>
<td>0.069</td>
<td>1.875</td>
<td>0.030*</td>
<td>[0.011; 0.241]</td>
</tr>
<tr>
<td>H6: Organizational Readiness -&gt; Intention to Adopt</td>
<td>0.045</td>
<td>0.063</td>
<td>0.717</td>
<td>0.237</td>
<td>[-0.056; 0.152]</td>
</tr>
<tr>
<td>H7: AI Strategic Alignment -&gt; Intention to Adopt</td>
<td>0.126</td>
<td>0.058</td>
<td>2.161</td>
<td>0.015**</td>
<td>[0.030; 0.221]</td>
</tr>
<tr>
<td>H8: AI Awareness -&gt; Intention to Adopt</td>
<td>-0.032</td>
<td>0.043</td>
<td>0.734</td>
<td>0.232</td>
<td>[-0.100; 0.043]</td>
</tr>
<tr>
<td>H9: Higher Authority Support -&gt; Intention to Adopt</td>
<td>0.161</td>
<td>0.042</td>
<td>3.815</td>
<td>0.000***</td>
<td>[0.092; 0.231]</td>
</tr>
<tr>
<td>H10: Auditees Support x Task Technology Fit -&gt; Intention to Adopt</td>
<td>-0.040</td>
<td>0.043</td>
<td>0.931</td>
<td>0.176</td>
<td>[-0.102; 0.040]</td>
</tr>
<tr>
<td>H11: Task Characteristics -&gt; Task Technology Fit</td>
<td>0.139</td>
<td>0.038</td>
<td>3.681</td>
<td>0.000***</td>
<td>[0.083; 0.207]</td>
</tr>
<tr>
<td>H12: Task Technology Fit -&gt; Intention to Adopt</td>
<td>0.272</td>
<td>0.048</td>
<td>5.636</td>
<td>0.000***</td>
<td>[0.188; 0.346]</td>
</tr>
</tbody>
</table>

**H1: AI complexity negatively influences the Task-Technology Fit.**

H1 posits that AI complexity would have a negative significant impact on Task Technology Fit. The results show that AI complexity has a significant negative effect on Task Technology Fit (Path Coefficient: -0.094, t-value = 2.640, p-value = 0.004), supporting H1.
H2: *Perceived Scalability* positively influences the Task-Technology Fit.

In H2, we postulate that Perceived Scalability would have a significant positive impact on Task Technology Fit. The results show that Perceived Scalability has a significant positive effect on Task Technology Fit (Path Coefficient: 0.164, t-value = 3.351, p-value = 0.000). Hence, H2 was supported.

H3: *Relative Advantage* positively influences the Task-Technology Fit.

We posit that Relative Advantage would have a significant positive impact on Task Technology fit. The results show that Relative Advantage has a significant positive effect on Task Technology Fit (Path Coefficient: 0.444, t-value = 10.522, p-value = 0.000). Hence, H3 was supported.

H4: *Security concerns will influence the Intention to Adopt AI.*

Based on the data from Phase I and theoretical findings, we hypothesized that security concerns would impact the intention to adopt AI. The results confirmed a significant relationship (Path Coefficient = 0.092, P-Value = 0.023). This finding indicates that security concerns influence the intention to adopt AI. Hence, H4 was supported, demonstrating the importance of addressing security concerns in AI adoption.

H5: *Leadership support positively influences the Intention to Adopt AI tools.*

H5 hypothesizes that Leadership support would have a positive significant impact on Intention to Adopt AI. The results show that Leadership support has a significant positive effect
on the Intention to Adopt AI (Path Coefficient: 0.130, t-value = 1.875, p-value = 0.030). Hence, H5 was supported.

**H6: Organizational Readiness positively influences Intention to Adopt AI.**

H6 posits that Organizational Readiness has a positive significant impact on Intention to Adopt AI. The results show that Organizational Readiness has no effect on Intention to Adopt AI (Path Coefficient: 0.045, t-value = 0.717, p-value = 0.237). Hence, H6 was not supported.

**H7: AI Strategic Alignment positively influences the Intention to Adopt AI.**

H7 postulates that AI Strategic Alignment has a positive significant impact on Intention to Adopt AI. The results show that AI Strategic Alignment has a significant positive effect on Intention to Adopt AI (Path Coefficient: 0.126, t-value = 2.161, p-value = 0.015). Hence, H7 was supported.

**H8: AI Awareness will positively influence the Intention to Adopt AI.**

H8 posits that AI Awareness has a significant positive impact on the intention to adopt AI. The results show that AI Awareness has no effect on the Intention to Adopt AI (Path Coefficient: -0.032, t-value = 0.734, p-value = 0.232). Hence, H8 was not supported.

**H9: Higher Authority Support will positively influence the Intention to Adopt AI.**

H9 hypothesizes that higher authority support has a significant positive impact on the Intention to Adopt AI. The results show that Higher Authority Support has a significant positive effect on the Intention to Adopt AI (Path Coefficient: 0.161, t-value = 3.815, p-value = 0.000). Hence, H9 was supported.
H10: Auditees Support moderates the relationship between Task-Technology Fit and the Intention to Adopt AI Tools.

H10 postulates the moderating role of Auditees Support on the relationship between Task Technology Fit and the Intention to Adopt AI tools. The result revealed a negative and not significant impact of Auditees Support on the relationship between Task Technology Fit and the Intention to Adopt AI tools (Path Coefficient: -0.040, t-value = 0.931, p-value = 0.176). Hence, H10 was not supported.

H11: Audit Task Characteristics positively affect the Task Technology Fit.

H11 posits that Audit Task Characteristics would have a significant positive impact on Task Technology Fit. The results show that Audit Task Characteristics have a significant positive effect on Task Technology Fit (Path Coefficient: 0.139, t-value = 3.681, p-value = 0.000). Hence, H11 was supported.

H12: Task-Technology Fit positively affects the Intention to Adopt AI.

H12 postulates that Task Technology Fit has a positive significant impact on Intention to Adopt AI. The results show that Task Technology Fit has a significant positive effect on the Intention to Adopt AI (Path Coefficient: 0.272, t-value = 5.636, p-value = 0.000). Hence, H12 was supported.
6.5 Summary of Phase II Results

Our study's second research question (RQ2) is: “What are the outcomes of the factors influencing the intention to adopt AI?” This quantitative question aims to test and validate the factors identified in Phase I of our mixed-method research based on qualitative findings. We aim to provide an organization-wide perspective, primarily from the auditors' standpoint. Figure 8 illustrates the updated relationships in our research model, and Table 17 summarizes the results of the hypotheses. A more detailed discussion will be presented in Chapter 7.
As indicated by the research question and the results in this section, most of the relationships were confirmed and supported by the findings from Phase I. This confirms that our respondents in both phases shared most of the same factors affecting the intention to adopt AI tools within the GovAudit workflow system at SAB. However, AI Awareness, Organizational Readiness, and the moderation effect of Auditees' Support on the relationship between Task Technology Fit and Intention to Adopt AI tools were not supported.

Similarly, AI awareness did not exhibit a significant relationship with the intention to adopt AI. This implies that employees prioritize task completion efficiency over understanding AI concepts. This finding diverges from Phase I findings and existing literature expectations, which often emphasize the importance of AI awareness in facilitating adoption. It suggests that practical application and immediate benefits may be more influential in driving AI adoption than theoretical understanding.

Organizational readiness also did not show a significant relationship with the intention to adopt AI. This indicates that employees may value the efficiency and effectiveness of task completion more than the organization's preparedness for IT innovations. This result contrasts with Phase I findings and challenges existing literature that underscores the importance of organizational readiness in successful technology adoption. It highlights the need for further research to explore how organizational readiness impacts AI adoption in different contexts.

Moreover, the moderation effect of auditee support on the relationship between task technology fit and intention to adopt AI tools was not significant, contradicting Phase I findings. This suggests that auditors perceive higher authority support for AI implementation as
influential, potentially diminishing concerns about auditee hesitance once AI tools are implemented.

While some results align with Phase I findings, unexpected outcomes underscore the complexity of the factors influencing the intention to adopt AI tools within governmental organizations. This warrants a more profound exploration in the following chapters.

*Table 17. Summary of Hypotheses results*

<table>
<thead>
<tr>
<th>H#</th>
<th>Statement</th>
<th>Sign</th>
<th>p-value</th>
<th>Significance</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>AI complexity negatively influences the Task-Technology Fit.</td>
<td>(-)</td>
<td>0.004</td>
<td>**</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>Perceived Scalability positively influences the Task-Technology Fit.</td>
<td>(+)</td>
<td>0.000</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>Relative Advantage positively influences the Task-Technology Fit.</td>
<td>(+)</td>
<td>0.000</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>Security concerns will influence the intention to adopt AI.</td>
<td>(-)</td>
<td>0.023</td>
<td>*</td>
<td>Supported</td>
</tr>
<tr>
<td>H5</td>
<td>Leadership support positively influences the intention to adopt AI tools.</td>
<td>(+)</td>
<td>0.030</td>
<td>*</td>
<td>Supported</td>
</tr>
<tr>
<td>H6</td>
<td>Organizational Readiness positively influences intention to Adopt AI.</td>
<td>(+)</td>
<td>0.237</td>
<td></td>
<td>Not Supported</td>
</tr>
<tr>
<td>H7</td>
<td>AI Strategic Alignment positively influences the intention to adopt AI.</td>
<td>(+)</td>
<td>0.015</td>
<td>**</td>
<td>Supported</td>
</tr>
<tr>
<td>H8</td>
<td>AI Awareness will positively influence the intention to adopt AI.</td>
<td>(+)</td>
<td>0.232</td>
<td></td>
<td>Not Supported</td>
</tr>
<tr>
<td>H9</td>
<td>Higher Authority Support will positively influence the intention to adopt AI</td>
<td>(+)</td>
<td>0.000</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H10</td>
<td>Auditees Support moderates the relationship between Task-Technology Fit and the Intention to adopt AI Tools.</td>
<td></td>
<td>0.176</td>
<td></td>
<td>Not Supported</td>
</tr>
<tr>
<td>H11</td>
<td>Audit Task Characteristics positively affect the Task Technology Fit</td>
<td>(+)</td>
<td>0.000</td>
<td>***</td>
<td>Supported</td>
</tr>
<tr>
<td>H12</td>
<td>Task-Technology Fit positively affects the intention to adopt AI</td>
<td>(+)</td>
<td>0.000</td>
<td>***</td>
<td>Supported</td>
</tr>
</tbody>
</table>
CHAPTER 7: Discussion

In this chapter, we discuss the meta-inferences or the results of triangulating findings between the two phases of our mixed-method approach.

7.1 Conclusion of Study Results

This mixed-methods dissertation aims to identify and understand the key variables influencing the intention to adopt AI tools in auditing from a governmental organization's perspective. Phase I addressed RQ1 by identifying factors affecting the intention to adopt AI tools in auditing, resulting in a conceptual model. Phase II answered RQ2 by confirming these factors identified in the conceptual model. The final research question (RQ3) of our study asked, "Are the factors identified in the qualitative study, and as captured through our model, supported by the results of the quantitative study?" This question aims to analyze, discuss, and compare the results of both phases and draw inferences from them.

The results indicated overall support for many variables across both strands of our methodology, particularly concerning the roles of various technological, organizational, and environmental factors. The purpose of our mixed-methods research was developmental, using qualitative findings to shape the research model and hypotheses tested quantitatively (Creswell, 2003; Tashakkori & Teddlie, 1998; Venkatesh et al., 2013, 2016). Meta-inferences are presented and discussed below based on the results of both phases. Table 18 provides a detailed discussion of the development of Qualitative Inferences, Quantitative Inferences, and Meta-Inferences from our study based on the suggestion of the Guidelines for Conducting Mixed-Methods Research (Venkatesh et al., 2016).
Table 18. Development of Qualitative Inferences, Quantitative Inferences, and Meta-Inferences from Our Study (Adapted from Venkatesh, Brown, and Sullivan 2016)

<table>
<thead>
<tr>
<th>Category of Construct</th>
<th>Specific Construct</th>
<th>Qualitative Inference</th>
<th>Quantitative Inference</th>
<th>Meta-Inference</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technological</td>
<td>AI Complexity</td>
<td>Simplified tasks and increased user-friendliness can foster a positive attitude towards AI adoption among auditors. Conversely, AI tool complexity would negatively impact task technology fit.</td>
<td>Consistent with qualitative findings.</td>
<td>Technological factors related to the inherent characteristics of the AI tool technology for auditing will drive the Task-Technology Fit.</td>
<td>Our data analysis findings (from both phases) and existing literature confirm the impact of these factors on Task-Technology Fit (TTF) and AI tool adoption. These factors will enhance auditors' day-to-day work at SAB by increasing their output. Adopting AI tools will result in higher completion rates of audit tasks, greater efficiency in identifying anomalies in documents, and large-scale observation of auditees. Consequently, these technological factors play a significant role in influencing the TTF and adoption of AI tools.</td>
</tr>
<tr>
<td>Perceived Scalability</td>
<td>Focusing on scalability and AI integration in SAB's audit processes emphasizes task-technology fit, as the technology's capabilities align with and support the organization's tasks and objectives, positively influencing task-technology fit.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>AI tools will provide a technologically superior and efficient solution to their auditing requirement which will positively influence their Task Technology fit.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Security</td>
<td>The presence of security concerns in the implementation of AI tools influences the intention to adopt AI.</td>
<td></td>
<td>Results from Phase I and Phase II were both significant and the effect of Security on Intention to Adopt was established.</td>
<td>It appears that as the system is perceived to be more secure, the potential security risk is considered lower, thereby reducing security concerns. Consequently, a higher level of security (reflected by lower perceived potential security risks) leads to an increased intention to adopt AI tools.</td>
<td></td>
</tr>
<tr>
<td>Organizational</td>
<td>Leadership Support</td>
<td>When auditors feel that they have a supportive leadership, it will have a positive impact on the intention to adopt AI tools.</td>
<td>Consistent with qualitative findings.</td>
<td>Leadership's crucial role in AI adoption cannot be overstated. Their active support will overcome employee resistance and foster a positive attitude.</td>
<td>Ongoing leadership commitment is pivotal for successful AI integration and its benefits across the organization.</td>
</tr>
<tr>
<td>Organizational Readiness</td>
<td>Auditors believe that the organization's readiness to adopt AI will positively influence a seamless transition, enabling SAB to fully leverage AI's potential to achieve its objectives.</td>
<td>Organizational Readiness was not found to be significant.</td>
<td>Organizational Readiness from a wider organizational perspective has no direct effect on a governmental organizations intention to adopt AI tools in auditing.</td>
<td>This finding implies that employees prioritize task completion efficiency over organizational readiness for AI innovations, diverging from Phase I findings and existing literature expectations.</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>AI Strategic Alignment</td>
<td>Auditors believe that a well-defined AI strategic plan will positively influence the intention to Adopt AI.</td>
<td>Consistent with qualitative findings.</td>
<td>Well-defined AI strategies will drive the intention to adopt AI tools in auditing.</td>
<td>A well-defined strategic plan is crucial for successful AI integration, aligning initiatives with business strategy. Transparency between employees and leaders, along with a clear understanding of AI capabilities, are key.</td>
<td></td>
</tr>
<tr>
<td>AI Awareness</td>
<td>Auditors feel that AI awareness can better prepare and equip organizations to successfully integrate AI technologies and fully leverage their potential.</td>
<td>AI Awareness was not found to be significant.</td>
<td>AI Awareness for auditors has no direct effect on a governmental organizations intention to adopt AI tools in auditing.</td>
<td>This finding implies that employees prioritize task completion efficiency over understanding AI concepts AI innovations, diverging from Phase I findings and existing literature expectations.</td>
<td></td>
</tr>
<tr>
<td>Environmental Higher Authority Support</td>
<td>Higher Authority Support will lead to a positive influence on the intention to Adopt AI tools in Auditing for a governmental organization.</td>
<td>Consistent with qualitative findings.</td>
<td>Higher authority Support drives governmental organization adoption of AI tools in auditing.</td>
<td>Higher Authority Support presents a strong and positive role in the adoption of AI tools for governmental organizations.</td>
<td></td>
</tr>
<tr>
<td>Auditees Support</td>
<td>Auditees Support operates as a crucial intermediary, enhancing or hindering the alignment between task demands and the capabilities offered by AI technology.</td>
<td>Auditees Support moderating effect on Task Technology Fit and Intention to Adopt AI tools was not found to be significant.</td>
<td>Auditees support does not have an effect between the alignment of Task Technology Fit and Intention to adopt AI tools in auditing.</td>
<td>Auditees' support doesn't affect the relationship between Task Technology Fit and Intention to adopt AI, as indicated in Phase I. This is because the wider organization perspective could feel that auditees may feel compelled to use the new AI system regardless of their preference, given the push for AI adoption nationwide from the government under Saudi Vision 2030. Further, the lag period between phase I and phase II could’ve changed the perspectives of the respondents between the two phases.</td>
<td></td>
</tr>
<tr>
<td>Technology Fit Audit Task Characteristics</td>
<td>The Audit Task characteristics will positively affect the Task Technology Fit.</td>
<td>Consistent with qualitative findings.</td>
<td>The distinct characteristics of auditing underscore the necessity for technological advancement to streamline daily activities.</td>
<td>AI integration gains traction in the field of auditing, aligning AI capabilities with the unique characteristics of auditing tasks becomes instrumental in ensuring effective and efficient technology utilization.</td>
<td></td>
</tr>
<tr>
<td>Task-Technology Fit</td>
<td>Task Technology fit will positively influence the intention to adopt AI tools in Auditing.</td>
<td>Consistent with qualitative findings.</td>
<td>The results highlight a solid connection between Task Technology Fit (TTF) and intentions to adopt AI, emphasizing the crucial role of technological compatibility in driving the adoption process forward.</td>
<td>Ensuring alignment between Task Technology Fit (TTF) and AI technology is crucial for the successful adoption of AI by SAB auditors. Any mismatch between task requirements and AI technology could impede adoption, underscoring the necessity of this alignment to facilitate a seamless transition.</td>
<td></td>
</tr>
</tbody>
</table>

**Technological Factors**

The results from our developmental approach, transitioning from Phase I to Phase II, fully converged in many areas of our conceptual model. All Technological factors (AI complexity, Perceived Scalability, Relative Advantage, and Security) significantly affected the dependent variables, particularly the relationship between Task-Technology Fit (TTF) and the intention to adopt AI tools in auditing for governmental organizations. These technological factors, related to the inherent characteristics of AI tools, are crucial for driving TTF. They enhance auditors' day-to-day work at SAB by increasing their output, leading to higher completion rates of audit tasks, greater efficiency in identifying document anomalies, and large-scale observation of auditees. Consequently, these technological factors significantly influence the TTF and adoption of AI tools, as also highlighted in previous work (Alsheibani, Messom, & Cheung, 2020b; Kim et al., 2018; Picoto et al., 2014; C. Sharma et al., 2023; Wright et al., 2017; Zhu et al., 2006).
Moreover, security concerns also had a significant effect on the intention to adopt AI tools, consistent with findings from previous research (Alsheiabni et al., 2019; Pillai & Sivathanu, 2020). This indicates that addressing security concerns is crucial for facilitating AI adoption in auditing. The positive perception of security measures, likely due to leadership's proactive implementation of safeguarding measures, underscores the importance of organizational readiness in mitigating potential risks associated with AI adoption. This convergence between technological factors in Phase I and Phase II shows the comprehensive nature of our conceptual model in explaining the adoption of AI tools in governmental auditing contexts.

**Organizational Factors**

The results of our organizational factors differed between Phase I and Phase II. However, Leadership Support and AI Strategic Alignment were fully convergent across both methods and supporting literature (Horani et al., 2023; Jeyaraj et al., 2006; Kurup & Gupta, 2022; Pillai & Sivathanu, 2020; C. Sharma et al., 2023; Vasiljeva et al., 2021). The role of leadership in AI adoption for governmental organizations cannot be overstated. Their active support is essential for overcoming employee resistance and fostering a positive attitude toward AI. Leaders who champion AI initiatives and communicate the expected benefits and changes clearly can significantly ease the transition process.

Regarding AI Strategic Alignment, a well-defined strategic plan was found to be crucial for successful AI integration in governmental organizations. Aligning AI initiatives with the overall business strategy ensures that AI efforts are purposeful and contribute to the organization's goals. Transparency between employees and leaders about the AI adoption process
helps build trust and buy-in from staff. Additionally, clearly understanding AI capabilities and limitations enables the organization to set realistic expectations and effectively integrate AI tools into existing workflows. This comprehensive approach helps maximize the benefits of AI adoption and ensures that technological advancements are fully leveraged to improve organizational efficiency and effectiveness.

Results for Organizational Readiness and AI Awareness did not converge but instead diverged between Phase I and Phase II. When tested in Phase II, Organizational Readiness was found to have no direct effect on a governmental organization's intention to adopt AI tools in auditing. This finding suggests that employees prioritize task completion efficiency over organizational readiness for AI innovations, which diverges from the Phase I findings and existing literature (Seethamraju & Hecimovic, 2022). This divergence can also be attributed to the larger sample size in Phase II, where employees might not be concerned about whether SAB is prepared for AI tool integration. This assumption is plausible since most of our sample in Phase II were auditors (80%) compared to only four auditors in Phase I. Further research in similar contexts is necessary to determine whether Organizational Readiness impacts governmental organizations' intention to adopt AI tools.

Similarly, AI Awareness also showed a divergence between the phases and supporting literature (Alsheibani, Messom, & Cheung, 2020b; Rawashdeh et al., 2022; J. Yang et al., 2021). The results indicate that understanding AI awareness may not be as crucial to the broader organization as seen in the Phase II findings. The significant relationships between technological factors, audit task characteristics, and Task Technology Fit highlight that employees focus more on the practical benefits of AI for completing tasks efficiently rather than on comprehending AI concepts. This contrasts with Phase I, suggesting that practical application and efficiency drive
adoption more than theoretical understanding. It will be interesting to explore this further post-adoption to determine if AI awareness remains unnecessary.

*Environmental Factors*

For the environmental factors identified in Phase I, only Higher Authority Support showed full convergence between both phases and findings from supporting literature (Alsheibani, Messom, & Cheung, 2020b; Bose & Luo, 2011). Higher Authority Support emerged as a crucial driving force for adopting AI tools in auditing within governmental organizations. This strong and positive influence underscores the importance of backing from higher authorities in fostering technological adoption. The findings suggest that Higher Authority Support is pivotal for AI adoption and could also play a significant role in other technological adoption efforts within governmental organizations like SAB. This highlights higher-level support's broader applicability and importance in successfully integrating new technologies across various governmental functions. Further research could explore how this support can be effectively leveraged to facilitate other technological advancements in similar contexts.

Regarding Auditees Support, Phase I suggested that a lack of support from Auditees could hinder the integration and adoption of new AI tools. However, our Phase II analysis revealed that Auditees' support does not impact the alignment between Task Technology Fit and the intention to adopt AI tools in auditing. This indicates that Auditees' support does not affect the relationship between Task Technology Fit and the intention to adopt AI, contrary to Phase I findings. One possible explanation is that the broader organizational perspective in Phase II reflects a belief that Auditees may feel obligated to use the new AI system regardless of their personal preferences. This is likely due to the government's nationwide push for AI adoption.
under Saudi Vision 2030, which will compel auditees to comply with the new AI-enabled system when conducting SAB’s audit tasks. This mandated compliance diminishes the impact of Auditees' support on the successful adoption of AI tools.

Further, the temporal gap between Phase I and II may have significantly altered the respondents' perspectives. Over time, new information, changing circumstances, or an evolving technological climate can influence an individual's viewpoint. Consequently, the respondents' answers in Phase II might reflect these perception shifts, leading to variations in their responses compared to Phase I. It would be interesting to conduct a future study post-adoption at SAB to assess if Auditees' support has an impact.

Task Related Factors

Results of the TTF theory variables identified in Phase I were fully convergent between both phases, emphasizing the crucial role of technological compatibility in driving the adoption process forward. The distinct characteristics of auditing underscore the necessity for technological advancement to streamline daily activities. As AI integration gains traction in auditing, aligning AI capabilities with the unique characteristics of auditing tasks becomes instrumental in ensuring effective and efficient technology utilization. The results highlight a solid connection between Task Technology Fit (TTF) and intentions to adopt AI, indicating that any mismatch between task requirements and AI technology could impede adoption. Therefore, ensuring alignment between Task Technology Fit (TTF) and AI technology is crucial for governmental organizations' successful adoption of AI in Auditing, facilitating a seamless transition.
In conclusion, our mixed-methods approach has provided comprehensive insights into the factors influencing the intention to adopt AI tools in auditing within governmental organizations. We identified and validated several variables through qualitative and quantitative analyses, particularly in Technological, Organizational, and Environmental factors. While some variables, such as Leadership Support and AI Strategic Alignment, exhibited full convergence across phases, others, like Organizational Readiness and AI Awareness, showed divergence in their effects on AI adoption intentions. The findings underscore the crucial role of technological compatibility in driving the adoption process forward, as highlighted by the TTF theory. Aligning AI capabilities with the unique characteristics of auditing tasks is essential, as any mismatch between task requirements and AI technology could impede adoption.

Additionally, our study elucidates the influential role of Higher Authority Support in fostering AI adoption within governmental organizations. However, contrary to initial hypotheses, Auditees' support was found to have minimal impact on the alignment between Task Technology Fit and the intention to adopt AI tools. Overall, our findings provide valuable insights into the complex dynamics surrounding AI adoption in auditing, emphasizing the need to consider various factors to facilitate a seamless transition toward AI integration in governmental organizations.

7.2 Implications

7.2.1 Theoretical Implications

First, our research significantly contributes to the existing literature on organizational AI adoption by focusing specifically on the factors influencing AI tool adoption within governmental organizational settings, with a particular emphasis on auditing contexts (Gupta et
al., 2022; Horani et al., 2023; Phuoc, 2022; Pillai et al., 2022; C. Sharma et al., 2023). While previous research has predominantly examined AI adoption in private and public sector organizations, our study offers a novel perspective that expands the current theoretical framework. By delving into a governmental bureaus' unique challenges and opportunities, we provide valuable insights that contribute to a more nuanced understanding of AI adoption dynamics.

Second, our research capitalizes on the distinct characteristics of the governmental bureau under study, allowing us to generate further insights into the factors influencing the intention to adopt AI. This approach broadens our understanding of AI adoption factors and underscores the importance of studying government organizations as key players in the AI adoption landscape. Moreover, our findings hold relevance beyond the specific context of the studied bureau, offering valuable insights for similar agencies in other countries, particularly those within the GCC region, where contextual similarities to Saudi Arabia are apparent.

Third, our study breaks away from the conventional focus on expert perspectives that often characterize prior research on AI adoption (Demlehner & Laumer, 2020; Hradecky et al., 2022; Merhi, 2023). Instead, we shift the spotlight to end-users of AI tools, providing valuable insights into the factors affecting AI adoption from the user's viewpoint. By centering our analysis on the experiences and perspectives of end-users, we contribute to a more comprehensive understanding of the complexities surrounding AI adoption processes. This user-centric approach adds depth to the existing literature, highlighting the importance of considering user perceptions and experiences in shaping successful AI adoption strategies.
7.2.2 Practical Implications

First, the findings from our research offer practical advantages to the governmental auditing agency in our case study. The agency can facilitate a smoother transition toward AI adoption and promote successful implementation by understanding the factors influencing AI adoption from their employees' perspectives (Gupta et al., 2022; Horani et al., 2023). Armed with this knowledge, the agency can tailor their strategies and interventions to address specific concerns and challenges related to AI adoption, ultimately enhancing organizational efficiency and effectiveness.

Second, governmental organizations with analogous setups stand to benefit significantly from our research findings. This includes other governmental agency bureaus in countries with regulatory bodies resembling our case study, such as countries in the GCC (Phuoc, 2022; Pillai et al., 2022; C. Sharma et al., 2023). Our research outcomes can assist these organizations in comprehending the factors that influence AI adoption, thereby aiding their decision-making processes and fostering a culture of innovation and adaptability.

Third, the study's exploration of cultural differences in AI adoption factors provides practical insights to senior-level managers and organizational leaders operating within multinational environments (Demlehner & Laumer, 2020; Hradecky et al., 2022). Organizations with global operations will gain a nuanced understanding of AI adoption dynamics across different regions, enabling them to develop more culturally sensitive and effective AI adoption strategies. By leveraging these cultural insights, organizations can navigate the complexities of AI adoption more successfully and capitalize on opportunities for growth and innovation.
7.2.3 Educational Implications

As for educational implications, our research serves as a rich case study within the Information Systems (IS) field, offering a valuable educational resource for students, educators, and researchers (Merhi, 2023; Lee, 2019). The complex interplay of factors in adopting AI tools, especially in the distinctive context of governmental auditing, provides an exemplary teaching tool for IS education. By analyzing real-world cases like ours, students and researchers can better understand the practical challenges and opportunities associated with AI adoption, empowering them to develop innovative solutions and contribute to advancing the field.
Chapter 8: Conclusion

In this chapter, we first provide a summarized statement of our dissertation. Then, we explore the study's contributions. Finally, we conclude with a discussion of the study's limitations and suggestions for future research.

8.1 Summary

AI has gained significant attention recently due to its potential to transform various sectors, including government organizations. Adopting AI in government organizations can improve efficiency, enhance decision-making, and improve service delivery. However, adopting AI faces significant challenges due to the complex nature of these technologies, which could limit its impact if not adequately addressed. Through a mixed-methods design and by developing a conceptual model of the intention to adopt AI tools in auditing for a governmental bureau in Saudi Arabia, our research provides strong evidence that various technological, organizational, and environmental factors influence AI adoption in such a culturally diverse and innovation-driven country.

Our study highlights several key factors that impact AI adoption. Technological factors such as the compatibility of AI tools with existing systems and the perceived usefulness of these tools play a crucial role in shaping the intention to adopt AI. Organizational factors, including leadership support and strategic alignment with AI initiatives, are also significant in facilitating AI adoption. Environmental factors, particularly the influence of higher authority support, further underscore the importance of a supportive external environment in driving AI adoption within governmental organizations.
Focusing on a governmental bureau in Saudi Arabia, our research also emphasizes the cultural context and its influence on AI adoption. The findings suggest that governmental entities’ unique cultural and organizational characteristics in Saudi Arabia necessitate tailored strategies for successful AI integration (Alotaibi & Alshehri, 2023). This context-specific insight is valuable for understanding how AI adoption efforts can be optimized in similar governmental settings across the GCC region and beyond. Beyond its specific context, our study provides universal insights applicable to governmental organizations worldwide. By systematically identifying key technological, organizational, and environmental factors influencing AI adoption, our research underscores essential challenges and strategic considerations for implementation success. The insights gained from Saudi Arabia's cultural and organizational nuances offer a foundational understanding of how these factors interact within diverse governmental settings, enabling the development of effective strategies for AI integration (Alotaibi & Alshehri, 2023; Dwivedi et al., 2021). This comprehensive approach enhances the generalizability of our conceptual model. It sets a framework for future research to advance AI adoption efforts across diverse cultural and regulatory landscapes, ultimately improving the efficiency and effectiveness of public sector operations on a global scale.

Our study serves as a starting point for further research on this topic, aiming to contribute to a deeper understanding of technology adoption efforts in governmental organizations within similar contexts. We hope our findings will encourage continued exploration and support for AI adoption in government settings, ultimately leading to more effective and efficient public sector operations. Additionally, future research could build on our conceptual model to explore AI adoption in different governmental sectors and cultural contexts, thereby enhancing the
generalizability of our findings and providing a more comprehensive understanding of AI adoption dynamics in the public sector.

8.2 Contributions

Our research makes several notable contributions to the existing literature on organizational AI adoption. First, it expands the theoretical framework by focusing on the unique factors influencing AI tool adoption within governmental organizational settings, particularly in the context of auditing (Gupta et al., 2022; Horani et al., 2023; Phuoc, 2022; Pillai et al., 2022; C. Sharma et al., 2023). We utilize the TOE framework and the TTF model as theoretical lenses to inform our conceptual model. Previous research has concentrated mainly on AI adoption in private and public sector organizations, but our study delves into governmental bureaus' specific challenges and opportunities. This perspective provides valuable insights and contributes to a more nuanced understanding of AI adoption dynamics in a governmental context.

Additionally, our research leverages the distinct characteristics of the governmental bureau under study, generating further insights into the factors influencing the intention to adopt AI. This approach underscores the importance of examining government organizations as key players in the AI adoption landscape. The findings from our study not only broaden our understanding of AI adoption factors but also offer relevant insights for similar agencies in other countries, especially within the GCC region, where there are contextual similarities to Saudi Arabia. This cross-contextual relevance enhances the applicability and generalizability of our research outcomes.

Moreover, our study diverges from the conventional focus on expert perspectives that have dominated prior research on AI adoption (Demlehner & Laumer, 2020; Hradecky et al.,
By shifting the spotlight to end-users of AI tools, we provide valuable insights into the factors affecting AI adoption from the user’s viewpoint. This user-centric approach enriches the existing literature by highlighting the experiences and perspectives of end-users, contributing to a more comprehensive understanding of the complexities surrounding AI adoption processes. It underscores the importance of considering user perceptions and experiences in shaping successful AI adoption strategies.

Furthermore, our research carries substantial practical implications beyond the specific context of our case study. The insights gained provide actionable benefits to governmental auditing agencies worldwide by offering a nuanced understanding of the factors influencing AI adoption as perceived by their employees (Gupta et al., 2022; Horani et al., 2023). This understanding supports a smoother transition toward AI integration and fosters effective implementation strategies. By addressing sector-specific concerns and challenges associated with AI adoption, agencies can significantly enhance their operational efficiency and effectiveness, thereby advancing auditing practices globally. This holistic approach ensures that the benefits of AI adoption extend beyond organizational boundaries, contributing to broader advancements in governmental auditing methodologies and practices.

Lastly, our research serves as a valuable educational resource within the Information Systems (IS) field (Merhi, 2023; Lee, 2019). The complex interplay of factors in adopting AI tools, particularly in the distinctive context of governmental auditing, provides an exemplary case study for IS education. By analyzing real-world cases like ours, students and researchers can better understand the practical challenges and opportunities associated with AI adoption. This educational contribution empowers future professionals to develop innovative solutions and
contribute to advancing the field, fostering a new generation of experts equipped to navigate the evolving landscape of AI adoption in government organizations.

8.3 Limitations

There are a few limitations to this study that should be noted. First, due to the uniqueness of the sample type, which is that of auditors in a government bureau, participants were chosen by the government organization for all phases of the dissertation. This limitation prevented us from independently selecting participants for Phase I and II. In Phase I, we were provided with 8 SAB employees based on our sample criteria. Although we were able to communicate with them directly to set up interviews and obtain consent forms, we had limited control over the selection process. For Phase II, we could not directly send the surveys to participants. Instead, the survey link was sent to a key representative at SAB, who then distributed it to auditors based on our specific sample criteria for Phase II, which excluded those who participated in Phase I. We attempted to minimize this limitation in Phase I by explaining to our interviewees that their answers would not be shared with SAB and that they had complete control and flexibility during the interview process. In Phase II, we included a consent form reiterating that their answers would not be shared with SAB and that no identifying information would be obtained. Additionally, we incorporated two attention-check questions in the survey to filter out inattentive respondents.

Second, our study has a small sample size for Phase I of our qualitative study, consisting of only 8 participants. Ideally, we preferred more participants in Phase I to develop a more comprehensive conceptual model to test in Phase II. However, due to constraints imposed by our collaboration with SAB, we were limited to the number of participants provided. Nonetheless,
the larger sample size in Phase II helped to compensate for this limitation in our analysis. This led us to choose a dominant-less-dominant design for our mixed-method dissertation, allowing us to triangulate findings from both phases and enhance the overall validity of our results. Additionally, despite the small sample size in Phase I, our analysis revealed a significant degree of consensus among participants from both phases, further supporting the robustness of our findings.

Third, the study is conducted within a specific governmental bureau in Saudi Arabia, which may have unique cultural and organizational characteristics not present in other organizations. These distinctive factors might limit the applicability of the findings to other governmental organizations or different cultural contexts found elsewhere. The unique bureaucratic processes, hierarchical structures, and cultural norms in Saudi Arabia could influence the adoption and implementation of AI tools differently compared to other regions or countries. Therefore, examining how the identified conceptual model performs in various contexts and organizations undergoing AI adoption would be insightful. Future research could apply this model to different governmental agencies and sectors in other countries to assess its generalizability and to understand the potential variations in AI adoption influenced by diverse organizational and cultural environments.

8.4 Future Research

A longitudinal study focusing on the AI adoption journey of governmental organizations could provide valuable insights into the dynamics of AI implementation over time. This study could involve tracking organizations from the pre-adoption phase through the implementation process to the post-adoption phase. By examining the challenges, successes, and changes
experienced by organizations at different stages of the adoption journey, researchers can gain a
deep understanding of the factors influencing AI adoption and its long-term impact on
organizational practices and outcomes.

Future studies could also investigate the transferability of our conceptual model on the
intention to adopt AI tools in auditing to governmental sectors outside of Saudi Arabia,
particularly those undergoing similar adoption processes. Examining the model's applicability
across different sectors would validate its effectiveness and uncover sector-specific factors
influencing AI adoption. By broadening the scope of our research beyond auditing, researchers
can contribute to a more comprehensive understanding of the dynamics influencing AI adoption
across diverse governmental organizations. This approach enhances the theoretical robustness of
the model and offers practical insights for policymakers and practitioners globally.

Future studies could investigate how the integration of AI tools affects the compensation
and job satisfaction of SAB auditors. Specifically, researchers could explore the application of
the Expectancy Theory (Vroom, 1964) in governmental organizations that offer compensation
bonuses, such as SAB, concerning AI adoption. By examining how perceptions of rewards and
incentives influence employees' attitudes and behaviors toward AI adoption, researchers can
provide valuable insights into the role of motivational factors in driving technology adoption
within governmental contexts. This research could inform strategies for effectively incentivizing
AI adoption and maximizing its benefits for organizational performance and employee well-
being.
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Appendices
Appendix A: Mixed Methods Approach – Elaboration of Decision Choice

Elaboration of Decision Choice of Mixed-Methods Study Adapted from (Venkatesh et al. 2016)

<table>
<thead>
<tr>
<th>Step 1: decide on the appropriateness of mixed-methods research</th>
<th>Property</th>
<th>Decision Consideration</th>
<th>Other Design Decision(s) Likely to Affect Current Decision</th>
<th>Design Decision and Reference to the Decision Tree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Research questions</td>
<td>Qualitative or quantitative method alone was not adequate for addressing the research question of the factors affecting intention to adopt AI from the perspective of a governmental organization in a developing nation. Thus, we used a mixed-methods research approach.</td>
<td>None</td>
<td>➢High level Research Question: What are the factors that could affect the intention to adopt an AI system that would handle auditing tasks for current auditors in an organization?</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>➢We will be exploring the different multifaced factors affecting the adoption of AI solutions for auditors working in an Auditing governmental bureau in Saudi Arabia using a mixed-method approach (interviews/surveys).</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>➢The qualitative study will assist in building the research model concerning the intention to adopt AI from the organizations perspective to be tested on larger sample within the same organization using a quantitative approach.</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>➢The uniqueness of our case study (High authoritative Governmental auditing organization in a developing nation) requires a mixed method approach to enrich our understanding of these unique factors concerning their intention to adopt an AI system to replace their current system.</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>➢We wrote the qualitative and quantitative research questions separately first and a mixed-methods research question second.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>➢The qualitative research question was: What organizational factors influence a governmental agency's intention to adopt AI in its current workflow system?</td>
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<td></td>
<td></td>
<td></td>
<td>➢The quantitative research question was: What are the outcomes of these organizational factors influencing the intention to adopt AI</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>➢The mixed-methods research question was: Are the factors identified in the qualitative study, and as captured through our model, supported by the results of the quantitative study?</td>
<td></td>
</tr>
</tbody>
</table>
We wrote the research questions in the question format.

The quantitative research question was based on results from the qualitative research questions, and the mixed-methods research question depended on the results from both the quantitative and qualitative research questions.

The relationships between the questions and the research process were predetermined.

<table>
<thead>
<tr>
<th>Purpose of mixed-methods research</th>
<th>The purpose of our mixed-methods design was to help develop hypotheses for empirical testing using the results of the qualitative study given the uniqueness of the context of our case study.</th>
<th>Research questions</th>
<th>Developmental purpose and the results from the qualitative strand were used to develop the research model and the hypotheses tested in the quantitative strand.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epistemological perspective</td>
<td>The qualitative and quantitative components of the study used different paradigmatic assumptions.</td>
<td>Research questions, purposes of mixed methods</td>
<td>Multiple paradigm stance.</td>
</tr>
<tr>
<td>Paradigmatic assumptions</td>
<td>The researchers believed in the importance of research questions and embraced various methodological approaches from different worldviews.</td>
<td>Research questions, purposes of mixed methods</td>
<td>Dialectic stance (we used more of the interpretive and grounded-theory perspective in the qualitative study and then applied a positivist perspective and deductively tested the developed model in the quantitative study).</td>
</tr>
</tbody>
</table>

**Step 2: develop strategies for mixed-methods research designs**

| Design investigation strategy   | The mixed-methods study was aimed to develop and test a research model containing the factors affecting the intention to adopt. | Research questions, Paradigmatic Assumptions | ➤Study 1: Exploratory investigation. (Qualitative)  
➤Study 2: Confirmatory investigation. (Quantitative) |
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</tr>
</thead>
<tbody>
<tr>
<td>Strands/ phases of research</td>
<td>The study involved multiple phases</td>
<td>Purposes of mixed-methods research</td>
<td>Multistrand design.</td>
</tr>
<tr>
<td>Mixing strategy</td>
<td>The qualitative and quantitative components of the study were mixed at the data-analysis and inferential stages.</td>
<td>Purposes of mixed-methods research, strands/phases of research</td>
<td>Partially Mixed method</td>
</tr>
<tr>
<td>Time orientation</td>
<td>We started with the qualitative phase, followed by the quantitative phase.</td>
<td>Research questions, strands/ phases of research</td>
<td>Sequential (exploratory) design</td>
</tr>
<tr>
<td>Priority of methodological approach</td>
<td>The qualitative and quantitative components were not equally important.</td>
<td>Research questions, strands/ phases of research</td>
<td>Dominant-less dominant design with the quantitative study being the more dominant paradigm.</td>
</tr>
<tr>
<td>Step 3: develop strategies for collecting and analyzing mixed-methods data</td>
<td>Sampling design strategies</td>
<td>The samples for the qualitative and quantitative components differed, but came from the same governmental organization with those in the qualitative sample excluded from the quantitative sample (Parallel Samples).</td>
<td>Design investigation strategy, time orientation</td>
</tr>
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</tbody>
</table>
|  | Data collection strategies | ➢ Qualitative data collection in the first phase.  
➢ Quantitative data collection in the second phase. | Sampling design strategies, time orientation, strands/phases of research | ➢ Qualitative phase: semi-structured open-ended questions using a pre-designed interview guidelines.  
➢ Quantitative phase: closed-ended questioning (i.e., traditional survey design) |  |
|  | Data analysis strategy | • We analyzed the qualitative data not by “transformation” but by reducing it to broad categories using a software, ATLAS.Ti  
• We analyzed the qualitative data first and the quantitative data second. | Time orientation, data collection strategy, strands/phases of research |  | Sequential qualitative-quantitative analysis. |
| Step 4: draw meta-inferences from mixed-methods results | Types of reasoning | In our analysis, we focused on developing and then testing/confirming hypotheses. | Design-investigation strategy | Both inductive and deductive theoretical reasoning. (Started with an Abductive approach) |
|  | Inference quality | • The qualitative inferences met the appropriate qualitative standards.  
• The quantitative inferences met the appropriate quantitative standards.  
• We assessed the quality of meta-inferences. | Mostly primary design strategies, sampling-design strategies, data collection strategies, data analysis strategies, type of reasoning | ➢ We used conventional qualitative and quantitative standards in ensuring the quality of our inferences.  
➢ Design and explanatory quality; sample integration; inside-outside legitimation; multiple validities, weakness minimization. |  |
| Step 5: assess the quality of meta-inferences | Inference quality | We discussed all potential threats to inference quality in the form of limitations. | Data-collection strategies, data-analysis strategies | Threats to sample integration; sequential legitimation |
| Step 6: discuss potential threats and remedies | Inference quality |  |  |  |  |
Appendix B: Mixed Methods Approach – Quality Criteria

Mixed-Methods Approach and Criteria Adapted from (Venkatesh et al. 2013)

<table>
<thead>
<tr>
<th>Quality Aspects</th>
<th>Quality Criteria</th>
<th>Authors’ Response to Venkatesh et al. (2013) Guidelines</th>
</tr>
</thead>
</table>
| Purpose of mixed method approach       | Development                              | The study was divided into two phases:  
1) Qualitative Phase: Focusing on interview to identify the factors the influence the intention to adopt AI from an auditing governmental perspective in a developing nation and then develop a model and hypothesis to be tested.  
2) Quantitative Phase: Large quantitative survey confirming the factors identified from the previous phase. |
| Sequential less-dominant qualitative followed by dominant quantitative investigation | The scope and objectives of the qualitative investigation using an exploratory case study is very limited with a smaller sample size and it is primarily to support the quantitative investigation with a larger sample size. |
| Design quality                         | Design suitability/ appropriateness       | The study used qualitative semi-structured interviews based on theoretical lenses of adoption theories as part of an “exploratory case study” followed by a quantitative survey. This strategy of examining “raw” data from the phenomenon as a “prelude” to the larger quantitative study ensured that the research model tested using the quantitative study was relevant to the phenomenon of interest (Yin 2003, Wunderlich et al. 2019)  
In doing so, it sought to combine the advantages of the two approaches, achieving depth and insight into the phenomenon as well as the breadth of coverage. |
| Design adequacy                        | Qualitative                              | ➢ *Selection of a suitable organization:* SAB was selected because 1) it is a governmental organization planning to adopt an AI technology to replace their current system 2) Governmental organization overseeing the auditing of other public and private agencies in a developing nation.  
➢ *Entering the field with credibility:* official e-mail exchange between us and the responsible manager at the governmental bureau (SAB) who gave us permission to interview their employees that they selected for us. Customer information was then obtained, and interviews were set up through emails in which we introduced the research as a collaborative project between our research team (Consists of One PhD Student that is fluent in English and Arabic) and SAB.  
➢ *Conduct of interview:* Based on a semi-structured interview guideline protocol that is aimed to be flexible to capture highlight relevant factors of adoption. (Flick 1998). |
<table>
<thead>
<tr>
<th>Analytical adequacy</th>
<th>Qualitative</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ A research model was constructed based on the organizational adoption theories and the qualitative findings.</td>
<td>➢ Transcription of data from Arabic to English.</td>
</tr>
<tr>
<td>➢ All constructs measured using well-established scale.</td>
<td>➢ Relevant factor codes first generated by Atlas.Ti</td>
</tr>
<tr>
<td>➢ Appropriate sampling frame and sample size chosen.</td>
<td>➢ Labeling and re-labeling of the relevant concepts was an iterative process that took several rounds until no new concepts emerged.</td>
</tr>
<tr>
<td>➢ Triangulation of data from the many interviews.</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Quantitative</th>
<th>Qualitative</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ Justification of the choice of analysis technique (PLS).</td>
<td>➢ The constructs identified through the qualitative study were not only plausible, but many of them were seen to be relevant in the organization wide survey with the rest of SAB Auditors.</td>
</tr>
<tr>
<td>➢ Sufficient sample size of 490 to ensure reasonable power.</td>
<td></td>
</tr>
<tr>
<td>➢ Data was professionally collected and analyzed. We ensured that bias in sampling of subjects is avoided or at least minimized.</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Explanation Quality</th>
<th>Qualitative inference</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ Reliability Analysis was found to be sufficient and the results for Cronbach’s Alpha and Composite Reliability of both metrics exceed the required threshold of 0.70.</td>
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</tr>
<tr>
<td>➢ Convergent validity was found not to be a concern in our sample and all results were satisfactory and above the .5 AVE threshold.</td>
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<td>➢ Discriminant Validity was found not to be a concern and was tested using: 1) Fornell and Larcker Criterion. 2) HTMT.</td>
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<th>Quantitative inference</th>
<th>Integrative inference</th>
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<tbody>
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<td>➢ Many of the identified factors from the qualitative study were significant in the quantitative study. The R-square of the model was good. Based on the above, we can say that we have been able to achieve a reasonable degree of balance between comprehensiveness and parsimony in the model, and hence integrative efficacy. The synergy between the qualitative interviews, which explored the intention to adopt AI tools in auditing for a governmental bureau, and the subsequent organization-wide survey provides a comprehensive perspective. The quantitative results, interpreted in light of the qualitative findings, demonstrate a satisfactory level of integrative efficiency and efficacy. This indicates that our mixed-methods approach effectively captured the factors influencing AI adoption within the organization.</td>
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Appendix C: Qualitative Phase – Interview Questions

Interview Questions
(Bulleted questions function as potential additional probes for further exploration of the primary question, if needed)

- Demographic information (Age, Job Position, Work Experience, Degree level)?
- What do you know about artificial intelligence?
  - How would you define AI?
  - What are your biggest fears (If any) concerning adopting AI technology at SAB?
  - Are there any benefits you hope such technology can provide for SAB?
- Do you have any experience using AI technology? If so, can you briefly describe your experience?
  - If not, what other technologies do you use at SAB?
  - Possible Follow-Ups:
    - What were its strengths and weaknesses?
    - What features would you look forward to when using AI technology at SAB?
- What technological factors currently limit (if any) your capacity to do your job at SAB?
  - What are your biggest concerns when adopting a new technology at SAB?
  - Are there any security concerns with the current technology being used at SAB?
  - Do you feel ready for any technological transformation using AI at SAB when doing your job?
  - Do you believe that AI could help in assisting with your everyday tasks at SAB?
- What are your biggest concerns when proposing a major organizational transformation of the current system setup at SAB?
  - How much are you satisfied with the current auditing system at SAB? Is there still room for improvement?
  - What are the current strengths and weaknesses of the current system used for auditing?
  - Do you believe that you are ready for an AI transformation at SAB?
o In your opinion, are the current resources available to SAB sufficient for this transformation?

o What are the biggest barriers to implementing new technology such as AI in your organization?

- Is there currently any governmental pressure to adopt AI technology in Saudi Arabia?
  
  o Do you believe that SAB could benefit from adopting AI to aid in the auditing tasks?
  
  o Do you feel there is governmental support for SAB in adopting such technology?
  
  o Do you feel that the current working environment at SAB is suited to adopt AI technology?

- What are the advantages of SAB adopting AI to assist in the auditing task?
  
  o Do you feel there could be compatibility issues with current systems?
  
  o Do you have concerns about the complexity of a new system?
  
  o What is the relative advantage that SAB can achieve by using AI technology to assist in the auditing job in your opinion?
  
  o Are there any concerns regarding the transparency of the AI system algorithm when outputting the auditing results?
Appendix D: Qualitative Phase – Details of Interviewees

Details of Interviewees

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Appendix E: Qualitative Phase - Coding Diagram

First-Order Concepts

- Chain of task operations must be clear
- The system must be easy to use
- UI must be clear and readable
- AI will help in increasing auditing tasks completion rate
- AI will help in reducing workload
- AI can automatically capture audit irregularities or issues
- AI will automate audit tasks
- Generates and tracks complete auditor details and allocates tasks
- Tracking and Notifying changes related to documents
- AI Doesn’t Make Mistakes
- AI Reduces Auditor Error Rate
- AI helps in decision making
- AI helps to identify missed areas of interest
- AI provides better data analysis capabilities
- AI will improve audit task quality output
- Data Breach and Information Security fears
- Network Security and Intrusions

Second-Order Concepts

- AI Complexity
- Perceived Scalability
- Auditing Automation
- Security

Aggregate Dimensions

- Technological
- Organizational
- Environmental

Organizational Readiness

- AI Awareness
- Leadership Support
- Strategic AI Implementation

Technological

- Financial Readiness
- Technical Capability of Auditor
- Technical Infrastructure
- Relates AI to Augmented Human Capabilities
- Relates AI to Big Data
- Relates AI to Intelligent Systems and devices
- Relates AI to Mobile App Engagement
- Active Leadership Support and Feedback-driven Culture
- Trust in the Management for a smooth AI transformation
- Perception of Employee Acceptance and Support of AI implementation
- Pre-implementation planning of AI tools is needed
- There is Methodology as Fear Mitigators for AI transparency
- Transition and Adaptation Challenges

Environmental

- Auditees Confusion and Miscommunication
- Auditees Operational Inefficiencies
- Auditees Technical and Infrastructure issues
- Government has invested highly in its Cyber Security capabilities
- Government-Supported Digital Transformation and AI Integration

Auditees Support

Higher Authority Support
## Appendix F: Qualitative Phase – Emergent Themes by Respondents

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<td>AI provides better data analysis capabilities</td>
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Appendix G: Quantitative Phase – Information Sheet

Exploring Factors Influencing the Adoption of AI Tools in Auditing
Information Sheet for Participants

Dear Participant,

We invite you to participate in our research study survey regarding the factors affecting the intention to adopt AI tools for auditing in a governmental organization. Before you decide to participate, we would like to provide you with some important information about the survey. Please take a moment to read the following information carefully. If you have any questions or concerns, do not hesitate to contact us using the provided contact information.

Purpose of the Survey:
The purpose of this survey is to provide answers to the factors affecting the intention to adopt AI tools for auditing in a governmental organization. We will be exploring the different multifaced factors affecting the adoption of AI factors for auditors working in an Auditing governmental bureau in Saudi Arabia using a survey. Your valuable input will help us confirm our findings regarding the factors that affect the intention to adopt AI tools for auditing. The results will be written up for a PhD Degree dissertation.

Participant Eligibility:
To participate in this survey, you must meet the following criteria:
- A full-time employee at SAB.
- Must be 18 and over.
- An Auditor, or Team-Leader with Auditing Duties.

Survey Procedure:
- The survey consists of 62 questions.
- It should take approximately 10 minutes to complete.
- All questions are optional, and you may skip any that you do not wish to answer.
- Your responses will remain confidential and anonymous. Your identity will not be linked to your survey responses.
- The survey may be completed online.
- If you encounter any technical difficulties or have questions while taking the survey, please contact Fahad Alsudairi at alsudairif@vcu.edu.

Data Privacy and Confidentiality:
- Your participation in this survey is voluntary.
- Your responses will be kept strictly confidential.
- Survey data will be stored securely and accessible only to authorized researchers.
- No personally identifiable information will be collected unless explicitly stated and necessary for the research purpose.
- Data will be reported in aggregate, and your individual responses will not be identifiable.

Risks and Benefits:
- There are no known risks associated with participating in this survey.
- By participating, you may contribute to valuable research and help improve our research findings.
**Consent:**
- Your decision to participate in this survey is entirely voluntary.
- If you agree to participate, please click the "I agree" button at the beginning of the survey.
- If you do not wish to participate, please do not continue with the survey.

**Contact Information:**
If you have any questions or concerns about this survey or need further information, please contact:

Fahad Alsudairi
Ph.D. Candidate
Department of Information Systems
School of Business
Virginia Commonwealth University
alsudairif@vcu.edu

Victoria Yoon, Ph.D.
Professor
Department of Information Systems
School of Business
Virginia Commonwealth University
vyyoon@vcu.edu

**Ethical Considerations:**
This survey has been approved by The Virginia Commonwealth University Institutional Review Board (IRB), and we are committed to adhering to ethical standards throughout the research process.
Thank you for considering participating in our survey. Your input is invaluable, and we appreciate your time and effort.

Sincerely,
Fahad Alsudairi
Ph.D. Candidate
Department of Information Systems – School of Business
Virginia Commonwealth University

*Do you agree to the above terms? By clicking I Agree, you consent that you are willing to answer the questions in this survey.*