World Journal of Research and Review (WJRR)
ISSN: 2455-3956, Volume-19, Issue-6, December 2024 Pages 08-15

The Skills Gap in AI-Driven IT Auditing: Implications for Workforce Training and Development

Olufunmilayo Adeyinka

***Abstract*—**

Purpose

The purpose of this paper is to examine the influence of perceived usefulness, ease of use, and organizational support on addressing the skills gap in AI-driven IT auditing among auditors in Nigeria.

Design/methodology/approach

The study employed a structured questionnaire targeting internal and external auditors, forensic auditors, and audit firm partners in Nigeria. Data collected were analyzed using regression analysis and descriptive statistics to evaluate the relationship between these factors and the auditors' skill gap.

Findings

The findings indicate that organizational support has a significant and positive impact on reducing the auditors' skills gap, while perceived usefulness and ease of use show no direct significant influence. These results highlight the critical role of institutional backing, including training initiatives and resource allocation, in enhancing auditors' capacity to utilize AI tools effectively.

Research limitations/implications

The study offers a framework for further research into workforce training and AI integration in auditing, emphasizing the need for longitudinal studies and broader sample diversity to explore additional influencing factors.

Practical implications

This study highlights the importance of tailored training programs, organizational investment, and leadership-driven initiatives in equipping auditors with the technical skills needed for AI adoption. It provides actionable recommendations for professional bodies, policymakers, and audit firms to address barriers such as high costs and inadequate training.

Social implications

The findings advocate for enhanced public awareness and equitable access to AI tools, enabling smaller audit firms to compete effectively in the digital auditing landscape.

***Index Terms*—AI-driven IT auditing, Auditors' skills gap, Organizational support, Perceived usefulness, Perceived ease of use.**

I. Introduction

The integration of Artificial Intelligence (AI) into IT auditing has rapidly transformed traditional audit practices, ushering in a new era of efficiency and precision (CGMA, 2018). AI technologies, such as machine learning algorithms and data analytics tools, have redefined audit workflows by automating routine tasks, detecting anomalies in vast datasets, and offering predictive insights to inform decision-making. These innovations enhance audit quality, streamline processes, and mitigate risks more effectively than traditional manual approaches (Eziefule et al., 2022; Abu Huson et al., 2024). However, this rapid technological shift has exposed a significant skills gap among auditors, many of whom are unprepared to leverage these advanced tools effectively. The growing reliance on AI in auditing highlights the urgent need for targeted workforce training and development to bridge this gap, ensuring auditors remain capable of meeting evolving industry demands (Adigwe et al., 2024; Abdelwahed et al., 2024).

The adoption of AI in IT auditing is part of a broader trend in the accounting and financial sectors, where emerging technologies such as blockchain and big data analytics have reshaped professional practices. AI's role extends beyond automation; it involves providing strategic insights that transform auditors from routine task performers into proactive decision-makers (Celestin & Vanitha, 2019; Han et al., 2023). However, this transition requires auditors to acquire new competencies in areas such as data science, machine learning, and IT systems auditing. The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks highlight factors such as perceived ease of use, performance expectancy, and facilitating conditions as critical determinants of technology adoption (Venkatesh et al., 2003; Afsay et al., 2023). Despite these theoretical advancements, the practical integration of AI tools in auditing remains hindered by a lack of training, technological complexity, and resistance to change among practitioners (Iwuanyanwu et al., 2023; Adelakun, 2022).

Ethical considerations and data privacy concerns further complicate the adoption of AI in auditing. As AI systems handle sensitive financial information and make decisions that directly impact organizational compliance and financial reporting, questions of transparency, accountability, and integrity become paramount (Adelakun, 2022; Onwubuariri et al., 2024). Additionally, the fear of job displacement due to automation exacerbates resistance among auditors, particularly those accustomed to traditional methods (Anomah et al., 2024). These challenges, combined with the technical demands of implementing AI-driven tools, highlight the need for comprehensive training programs that not only address technical skills but also cultivate ethical awareness and adaptability in the workforce (Abou-El-Sood et al., 2015; Afsay et al., 2023).

Workforce readiness is a critical factor in the successful adoption of AI technologies in auditing. However, existing training and development programs have failed to keep pace

Olufunmilayo Adeyinka

with technological advancements, leaving many auditors ill-equipped to utilize tools such as computer-assisted audit techniques (CAATs) and generalized audit software (GAS) (Mansour, 2016). Studies suggest that the implementation of AI-driven tools is often impeded by high costs, limited accessibility, and inadequate training on their practical applications (DeLone & McLean, 2003; Tijani, 2014). Bridging this gap requires a multifaceted approach, combining technical education with hands-on experience and continuous professional development. Effective strategies include integrating AI modules into academic curricula, offering industry-led training programs, and leveraging professional certification schemes to encourage skill acquisition among auditors (Payne & Curtis, 2016; Abu Huson et al., 2024).

The implications of failing to address the skills gap in AI-driven IT auditing are profound. Without sufficient training, auditors risk misinterpreting AI-generated insights, undermining audit quality and organizational trust. Moreover, the underutilization of AI tools diminishes their potential to enhance operational efficiency and reduce audit risks (Adelakun, 2022; Abdelwahed et al., 2024). The skills gap also presents broader economic challenges, as organizations that lag in adopting AI-driven auditing practices may struggle to compete in increasingly digital markets. Addressing these issues requires a concerted effort from industry stakeholders, academic institutions, and policymakers to align workforce capabilities with technological advancements (Eziefule et al., 2022; Abu Huson et al., 2024).

Ultimately, bridging the skills gap in AI-driven IT auditing is essential to safeguarding the profession's relevance and effectiveness in the digital age. By equipping auditors with the necessary skills to navigate complex AI systems and interpret their outputs accurately, organizations can ensure audit integrity, enhance compliance, and foster innovation (Adigwe et al., 2024; Iwuanyanwu et al., 2023). This study aims to contribute to this endeavor by examining the current skill levels of auditors, identifying gaps in existing training programs, and proposing a framework for targeted workforce development. By addressing these challenges, the research seeks to empower auditors to embrace AI technologies confidently, ensuring the continued evolution and resilience of the auditing profession in an increasingly technology-driven landscape (Onwubuariri et al., 2024).

II. Literature Review

a. Competency Level in AI-Driven IT Auditing

The evolution of auditing practices has been profoundly influenced by advancements in information technology and AI, which have reshaped the profession from manual processes into technology-driven methodologies. Historically, auditing focused on verifying financial records to assure stakeholders of the accuracy of financial statements (Lennox & Pittman, 2010). However, the emergence of complex financial systems and high-profile corporate scandals, such as Enron and Wirecard, exposed the limitations of traditional approaches, necessitating the integration of advanced technological tools into the auditing process (Abu Huson et al., 2024). These events highlightd the need for robust mechanisms to detect and mitigate sophisticated fraud schemes.

The integration of AI into IT auditing has transformed the scope and expectations of auditors. AI-driven tools now facilitate the analysis of vast datasets, enabling the detection of anomalies and predictive risk assessments with unparalleled precision (Iwuanyanwu et al., 2023). Unlike traditional methods reliant on manual inspection, these tools automate routine tasks, such as data reconciliation, freeing auditors to focus on strategic decision-making and risk mitigation (Eziefule et al., 2022). This shift has necessitated the adoption of frameworks like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), which highlight critical factors—such as perceived ease of use and performance expectancy—influencing auditors' acceptance of emerging tools (Venkatesh et al., 2003; Afsay et al., 2023).

Despite the potential of AI to enhance audit quality and efficiency, its adoption remains hindered by significant challenges, including a persistent skills gap among auditors. Many auditors lack the technical proficiency required to operate advanced AI tools or interpret their outputs effectively (Adigwe et al., 2024). This skills gap is exacerbated by the rapid pace of technological advancements, which demand continuous upskilling to ensure workforce relevance (Adelakun, 2022). Ethical concerns surrounding data privacy and transparency further complicate adoption, as auditors must navigate the complexities of safeguarding sensitive client information while maintaining compliance with regulatory standards (Onwubuariri et al., 2024).

Emerging technology tools such as Computer-Assisted Audit Techniques (CAATs) and Generalized Audit Software (GAS) have been instrumental in addressing some limitations of manual auditing processes. These tools support auditors by automating data analysis and offering client-specific insights, which enhance the efficiency of audit planning and execution (Adeyemi et al., 2014; Pedrosa & Costa, 2012). However, the adoption of these tools has been inconsistent, with barriers including high costs, complexity of implementation, and inadequate training programs limiting their effectiveness in practice (DeLone & McLean, 2003; Tijani, 2014).

The transition to AI-driven IT auditing has also expanded the auditor's role from verifying financial records to providing strategic advisory services. Leveraging AI tools, auditors can generate actionable insights, aiding organizations in decision-making and aligning operations with strategic goals (Celestin & Vanitha, 2019). This expanded scope requires auditors to develop not only technical expertise but also analytical and communication skills, further emphasizing the need for targeted workforce training and development (Eziefule et al., 2022).

Addressing the skills gap is imperative for fully realizing the benefits of AI in auditing. Organizations must prioritize the alignment of educational programs with emerging technologies, fostering a culture of adaptability and continuous learning. Effective strategies include industry partnerships to deliver practical training, curriculum updates in academic institutions to reflect technological demands, and the provision of incentives for professional development in AI-related competencies (Abou-El-Sood et al., 2015; Afsay et al., 2023). Bridging this gap will ensure auditors remain capable of delivering high-quality services in an increasingly complex and technology-driven business environment.

b. Organizational Investment in Workforce Development

The adoption of AI-driven IT auditing necessitates a comprehensive workforce transformation to address the skills gap and meet the demands of a rapidly evolving profession. Organizations must prioritize training programs that equip auditors with technical competencies to operate advanced AI tools and interpret their outputs effectively. For instance, integrating AI-focused modules into professional accounting and auditing curricula can prepare upcoming auditors, while current practitioners benefit from workshops and certifications targeting emerging technologies (Adigwe et al., 2024; Iwuanyanwu et al., 2023).

Collaboration among academia, professional bodies, and industry stakeholders is critical for aligning training programs with practical auditing demands. By leveraging partnerships, auditors can gain hands-on experience through real-world simulations and case studies, fostering their ability to use AI for tasks such as risk assessment and anomaly detection (Abu Huson et al., 2024). Furthermore, ethical considerations must be embedded into these initiatives. Auditors should understand the implications of AI use, including potential data biases, privacy concerns, and compliance challenges, ensuring informed decision-making and the maintenance of audit integrity (Adelakun, 2022).

The cultural shift within organizations is equally essential for workforce transformation. Leadership must foster adaptability and innovation, emphasizing AI as a tool to augment expertise rather than replace it. By investing in technology and creating an environment that values continuous learning, organizations can support auditors in adapting to AI integration (Anomah et al., 2024).

Emerging technologies like enterprise resource planning (ERP) systems and cloud computing have reshaped auditing practices, enhancing accessibility to e-data and improving decision-making. These technologies allow auditors to focus on value-added activities while automating routine tasks, ultimately improving audit efficiency and quality (Correia et al., 2019).

c. Technology Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis (1989), remains a widely used framework for analyzing technology adoption behavior. TAM posits that two primary factors influence an individual's acceptance of technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU reflects the extent to which individuals believe technology improves job performance, while PEOU captures the degree to which the technology is considered user-friendly and intuitive. These factors shape attitudes toward the technology, influencing behavioral intentions and actual adoption (Venkatesh et al., 2003; Mahzan & Lymer, 2014).

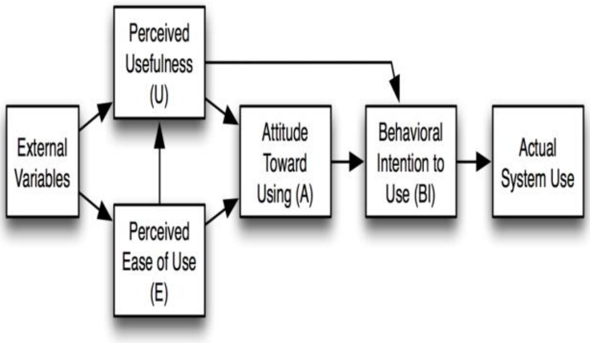

Figure 1: Technology Acceptance Model

Extensions of TAM, such as TAM 2 and TAM 3, have incorporated additional variables, including social influence, experience, and facilitating conditions, highlighting the importance of contextual factors in adoption decisions (Venkatesh & Davis, 2000; Abu Huson et al., 2024). Critics argue that TAM oversimplifies adoption behavior by neglecting professional environments where factors such as organizational culture, ethical considerations, and regulatory compliance also play pivotal roles (Adelakun, 2022; Anomah et al., 2024).

In AI-driven IT auditing, TAM is particularly relevant for addressing the challenges auditors face in adopting advanced tools. Many auditors report low PEOU due to insufficient training and limited exposure to AI systems, while unclear PU further hinders adoption, as auditors may fail to recognize the transformative impact of these tools on audit quality and efficiency (Adigwe et al., 2024; Iwuanyanwu et al., 2023). These challenges highlight the need for targeted training programs and user-centered designs to improve perceptions and accelerate adoption.

d. Perceived Usefulness

Perceived Usefulness (PU) is a central determinant of technology adoption, particularly in professional contexts where users evaluate the practical benefits of new tools. In auditing, PU refers to the extent to which AI tools enhance efficiency, accuracy, and decision-making. Advanced tools such as CAATs and Generalized Audit Software (GAS) have been shown to automate routine tasks, improve risk assessments, and reduce audit errors, thus enhancing overall audit quality (Correia et al., 2019; Smidt et al., 2021). However, smaller audit firms often perceive such investments as cost-prohibitive, particularly when immediate benefits are unclear (Abu Huson et al., 2024; Oni, 2015).

Empirical evidence demonstrates that AI tools significantly improve the timeliness and reliability of audit outcomes, particularly in data-intensive environments (Pedrosa et al., 2020). For instance, organizations using AI to streamline data analysis and fraud detection report measurable improvements in productivity and risk management (Eziefule et al., 2022). However, these benefits remain underutilized in smaller firms due to perceived barriers such as cost and complexity (Adigwe et al., 2024). Addressing these perceptions through clear communication of PU and offering affordable solutions is essential for wider adoption.

H1. The perceived usefulness of AI-driven IT audit

tools positively impacts auditors' skill gap.

e. Perceived Ease of Use

Perceived Ease of Use (PEOU) is another critical factor influencing technology adoption. In the context of AI-driven IT auditing, many auditors perceive advanced tools as overly complex and challenging to learn. This perception is particularly prevalent among traditional auditors with limited technical backgrounds, who may feel intimidated by the sophistication of AI systems (Mahzan & Lymer, 2014; Adigwe et al., 2024). Studies have shown that user-friendly interfaces and intuitive designs significantly enhance PEOU, making it a key consideration for technology developers (Kim et al., 2016; Widuri et al., 2016).

Training programs focusing on simplifying technology use and building auditor confidence have proven effective in overcoming PEOU-related barriers (Chopra, 2019; Abu-El-Sood et al., 2015). For example, hands-on workshops and guided tutorials can demystify AI tools, enabling auditors to navigate their functionalities with ease. Moreover, incremental adoption strategies—where auditors gradually incorporate AI into their workflows—have been shown to increase comfort and reduce resistance (Adelakun, 2022). Addressing PEOU is critical to ensuring that AI tools are accessible to auditors across varying levels of technical expertise.

H2. The perceived ease of use of AI-driven IT audit tools positively impacts auditors' skill gap.

2.6 Organizational Support

Organizational support plays a pivotal role in bridging the skills gap and facilitating the adoption of AI technologies. Leadership commitment to workforce development and technological innovation is critical for creating an environment conducive to change (Anomah et al., 2024). Investments in training, resources, and infrastructure enable auditors to build the competencies necessary for AI adoption. Studies highlight that organizations providing robust support systems—such as financial backing for certifications and time allowances for training—report higher adoption rates and improved audit outcomes (Adigwe et al., 2024).

Furthermore, organizations must actively address concerns around job displacement, emphasizing that AI serves to augment rather than replace human expertise (Adelakun, 2022). Clear communication and collaborative goal-setting between leadership and auditors help align expectations and reduce resistance. Organizations that foster a culture of adaptability and continuous learning are better positioned to integrate AI technologies successfully (Eziefule et al., 2022).

H3. Organizational support positively impacts auditors' skill gap in using AI-driven IT audit tools.

3. Theoretical Framework

This study's framework integrates TAM and its extensions to examine how factors like PU, PEOU, and organizational support influence the adoption of AI-driven IT auditing practices. By addressing these dimensions, the research highlights pathways to bridge the skills gap, enhance auditor performance, and optimize technology integration. The hypotheses developed reflect the interplay of individual perceptions, organizational factors, and technological challenges, providing a comprehensive approach to understanding adoption behavior in the context of AI-driven IT auditing.

III. Methodology

a. Sample and data collection

The study employed a primary data collection approach through a structured, close-ended questionnaire distributed via Google Forms, targeting a diverse cohort of internal and external auditors, audit firm partners, owners, and forensic auditors in Nigeria during 2024. Following the rule of thumb for sample size determination (Hair et al., 2010), the study estimated 150 participants but received 166 valid responses. The questionnaire was meticulously designed to assess participants' knowledge and experience regarding AI-driven IT auditing practices. Data cleaning and processing were performed to ensure quality and consistency before analysis. SPSS was utilized for statistical computations, incorporating advanced techniques such as bootstrapping to enhance reliability (Byrne, 2013). Descriptive statistics were employed to present demographic insights, while regression analysis using the General Linear Model (GLM) was adopted to simultaneously test multiple hypotheses. This comprehensive methodological approach underpins the study's robust examination of variables, ensuring credible insights into the research objectives (Venkatesh et al., 2003).

b. Sample selection

The sample for this study comprised qualified and partly qualified accountants and auditors with extensive experience in auditing organizations of various sizes. The focus on Nigerian auditors arises from the unique structure of the country's auditing industry, where smaller practice firms coexist with the Big 4, which dominate the market. Many smaller firms struggle to undertake large-scale or complex engagements due to a lack of technical proficiency, particularly in deploying IT auditing tools or managing AI-driven transactions (Adigwe et al., 2024). This challenge highlights the critical need to identify factors contributing to the skills gap, including training costs, time required for upskilling, availability of resources, and the high cost of advanced software. Addressing these barriers is essential for enhancing the capabilities of smaller firms and equipping their auditors to compete effectively. This study aims to provide actionable recommendations to bridge the gap and improve the adaptability of these firms.

c. Measurements

The survey comprised structured, close-ended questions that were adapted from validated prior studies to align with this study's framework. Section A included five demographic questions aimed at capturing participant profiles. Section B consisted of five questions assessing the level of awareness and perceived usefulness of IT auditing tools, while Section C contained five questions evaluating the perceived ease of use of AI-driven auditing technologies. Finally, Section D also comprised five questions examining the extent of organizational support for adopting these advanced tools. Each section was meticulously designed to align with the research objectives, facilitating comprehensive data collection to test the hypotheses and address the identified skills gap in AI-driven IT auditing.

d. Data Analysis

The data analysis for this study was conducted using a small sample size, which aligns with the use of regression analysis as it effectively accommodates multivariate studies and examines the cause-and-effect relationships between variables (Hair et al., 2010). A five-point Likert scale was employed to evaluate responses, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing participants to express the intensity of their agreement or disagreement with questionnaire items. This scale provides a robust framework for quantifying subjective data and is widely used in studies with similar designs (Pallant, 2001). The multivariate nature of the study necessitated this structured approach to evaluate how the independent variables influence auditing practices, ensuring clearer insights into the relationships between constructs.

E. Reliability and Validity

Reliability and validity tests were conducted to ensure the data was robust and free from significant errors. Reliability was measured using Cronbach's alpha, a standard metric for internal consistency. According to George and Mallery (2003), a Cronbach's alpha of 0.7 or higher is deemed acceptable, which aligns with the recommendations of Nunnally (1980). In this study, the Cronbach's alpha values for key constructs exceeded this threshold, demonstrating strong internal reliability. Validity was ensured by cross-verifying constructs across multiple instruments, reinforcing the robustness of the dataset and confirming its suitability for further analysis (Byrne, 2013). These measures establish the credibility of the data and provide a reliable foundation for hypothesis testing.

IV. Results

a. Descriptive statistics

The descriptive statistics from the study provide key insights into auditors' perceptions of IT auditing tools, AI-driven technologies, and organizational support. Overall, the results reveal strong agreement on the importance and utility of these tools, but with some variability across certain dimensions that highlight opportunities for improvement and targeted interventions.

The results for the awareness and perceived usefulness of IT auditing tools show a high mean score of 4.29, with a standard deviation of 0.72. This suggests that respondents generally recognize the significant role of IT auditing tools in improving audit quality and efficiency. Specifically, the statement "IT auditing tools improve the efficiency of audit tasks" received the highest mean of 4.65 (SD = 0.526), reflecting near-unanimous agreement among participants. Similarly, the tools' ability to enhance the accuracy of identifying anomalies and risk factors was rated highly (M = 4.31, SD = 0.979). These findings align with prior research that highlights the effectiveness of IT tools in reducing errors and improving decision-making in auditing (Abdelwahed et al., 2024).

However, the variability in responses, particularly for statements such as "Implementing IT tools significantly improves overall audit quality" (SD = 0.767), suggests that not all respondents have experienced the full potential of these tools. This could reflect disparities in access to or familiarity with advanced IT auditing tools, particularly among smaller firms, which often face resource constraints (Adelakun, 2022).

The mean score for the perceived ease of use of AI-driven technologies was 4.20, with a standard deviation of 0.69, indicating general agreement but slightly more variation than the previous category. Respondents agreed strongly that "AI technologies simplify complex auditing tasks" (M = 4.53, SD = 0.712) and "AI-driven auditing tools are easy to learn and use" (M = 4.53, SD = 0.694). This reflects positive perceptions of AI tools' potential to streamline auditing processes and improve efficiency.

However, the statement "The interface of these tools is intuitive and user-friendly" had a slightly lower mean score of 3.71 (SD = 0.834), suggesting that usability issues may be a barrier for some auditors. This aligns with the Technology Acceptance Model (TAM), which highlights that perceived ease of use is a key determinant of technology adoption (Venkatesh & Davis, 2000). Addressing interface challenges through user-centered design and training could further enhance adoption rates.

Organizational support was rated highly, with a mean score of 4.30 and the highest variability (SD = 0.75) among the three domains. The highest-rated item, "My organization actively supports training in IT and AI auditing" (M = 4.54, SD = 0.737), highlights the importance of training initiatives in fostering technology adoption. Similarly, respondents indicated strong agreement that organizations promote innovation and adaptability to new technologies (M = 4.53, SD = 0.677).

However, variability in responses to "Leadership encourages the adoption of advanced auditing tools" (M = 4.03, SD = 1.192) suggests inconsistency in leadership support across organizations. This finding reflects a potential challenge for smaller firms, which often lack the resources and leadership commitment to invest in advanced tools and training (Han et al., 2023). Enhancing leadership engagement could be a key step in overcoming these barriers.

The descriptive statistics reveal a positive perception of IT and AI-driven auditing tools, with high agreement on their usefulness and ease of use. However, variability in organizational support and usability highlights the need for targeted interventions, such as enhanced leadership engagement, user-friendly design, and comprehensive training programs. These findings align with existing literature emphasizing the importance of bridging resource and skill gaps to ensure equitable access to and effective adoption of advanced auditing technologies (Iwuanyanwu et al., 2023). By addressing these challenges, organizations can empower auditors to fully leverage technology, thereby enhancing audit quality and efficiency

b. Hypotheses testing

The regression analysis provides critical insights into the hypotheses related to the auditors' skill gap in using AI-driven IT audit tools. Starting with Hypothesis 1 (H1), which posits that the perceived usefulness of AI-driven IT audit tools positively impacts auditors' skill gap, the results do not provide evidence to support this hypothesis. The coefficient for perceived usefulness is **-0.077**, with a p-value of **0.148**, indicating that the relationship is statistically insignificant and, surprisingly, negative. This result suggests that perceived usefulness alone does not directly reduce the skill gap. It may imply that while auditors recognize the utility of these tools, this recognition does not necessarily translate into actionable improvements in their technical skills or the ability to utilize these tools effectively.

For Hypothesis 2 (H2), which suggests that the perceived ease of use of AI-driven IT audit tools positively impacts auditors' skill gap, the analysis shows a positive coefficient of **0.137**, but with a p-value of **0.166**, indicating that the relationship is not statistically significant. While the direction of the relationship aligns with the hypothesis, the insignificance highlights that ease of use, on its own, is insufficient to address the skill gap meaningfully. This finding highlights the need for additional interventions, such as training or hands-on practice, to complement ease of use perceptions in reducing the skill gap.

In contrast, Hypothesis 3 (H3), which proposes that organizational support positively impacts auditors' skill gap in using AI-driven IT audit tools, is strongly supported by the data. The coefficient for organizational training support is **0.278**, with a highly significant p-value of **<0.001**. The standardized beta value of **0.313** further emphasizes its robust impact. This result confirms that organizational support—such as providing training opportunities, resources, and a conducive environment—plays a critical role in reducing the skill gap. It highlights that the effective integration of AI tools into auditing practices relies heavily on institutional commitment and structured workforce development programs.

In conclusion, the regression analysis highlights that while perceptions of usefulness and ease of use are not directly significant in addressing the skill gap, organizational support emerges as the most influential factor. This finding reinforces the importance of targeted training and institutional backing in enabling auditors to effectively adopt and utilize AI-driven IT audit tools, addressing the skill gap comprehensively

V. Discussion

a. The perceived usefulness of AI-driven IT audit tools positively impacts auditors' skill gap

The results indicate that perceived usefulness of AI-driven IT audit tools has a statistically insignificant impact on reducing auditors' skill gap, as evidenced by a coefficient of **-0.077** and a p-value of **0.148**. This finding does not support the hypothesis that perceived usefulness positively influences auditors' skill gap. One plausible explanation could be that while auditors acknowledge the advantages of these tools, such as enhancing audit efficiency and accuracy (Abou-El-Sood et al., 2015; Adeyemi et al., 2014), their perception of usefulness does not translate into skill acquisition or usage. This misalignment might be due to a lack of adequate training or practical exposure to these tools (Betti and Sarens, 2021). Without tangible organizational structures or resources to implement these tools effectively, auditors might struggle to convert perceived usefulness into improved technical skills. Consequently, firms may need to supplement the perceived utility of AI tools with actionable training programs and demonstrations to bridge the gap between awareness and practical application.

b. The perceived ease of use of AI-driven IT audit tools positively impacts auditors' skill gap

Although the perceived ease of use of AI-driven tools shows a positive coefficient (**0.137**), the relationship is statistically insignificant (p-value = **0.166**). This suggests that ease of use alone does not significantly reduce the skill gap among auditors. This result challenges earlier studies that identified ease of use as a critical driver for technology adoption in auditing (Damerji and Salimi, 2021; Venkatesh and Bala, 2008). While ease of use might reduce the intimidation factor of learning new tools, the findings suggest that auditors require additional support, such as comprehensive onboarding and mentorship, to develop the necessary competencies. Moreover, younger auditors may find ease of use beneficial, but seasoned professionals accustomed to traditional methods may struggle to adapt without more structured guidance (Mahzan and Lymer, 2014). Organizations should ensure that training programs emphasize practical engagement with the tools, catering to diverse experience levels, to fully leverage the advantages of intuitive interfaces.

c. Organizational support positively impacts auditors' skill gap in using AI-driven IT audit tools

The hypothesis that organizational support positively impacts auditors' skill gap is strongly supported, with a significant coefficient of **0.278** and a p-value of **<0.001**. This finding aligns with previous literature highlighting the critical role of institutional backing in facilitating skill acquisition and technology adoption (Abiola, 2014). Factors such as consistent training, adequate resource allocation, and leadership encouragement significantly reduce the skill gap, as organizational support provides a conducive environment for learning and experimentation. For instance, auditors who receive technical support and training are better equipped to navigate the complexities of AI-driven tools, enhancing their competence and confidence (Mansour, 2016). Additionally, organizational support fosters a culture of adaptability and innovation, encouraging auditors to embrace emerging technologies (Omoteso, 2016). The findings emphasize that beyond individual perceptions, the institutional ecosystem plays a decisive role in equipping auditors with the necessary skills to meet the demands of AI-driven auditing environments.

In summary, while perceived usefulness and ease of use are important, their impact is limited without robust organizational support. The study highlights the necessity of a structured and supportive environment to bridge the skill gap in AI-driven IT auditing effectively. Organizational strategies should focus on integrating technology training into existing workflows, promoting collaboration, and providing accessible resources to ensure that all auditors, regardless of experience level, can adapt to emerging technological advancements.

VI. Conclusion

This study highlights the pressing skills gap in AI-driven IT auditing, underscoring the limited impact of perceived usefulness and ease of use on reducing the gap, while emphasizing the pivotal role of organizational support. Despite the recognized potential of AI tools to enhance efficiency and accuracy in auditing (Adigwe et al., 2024; Onwubuariri et al., 2024), their practical application remains constrained by inadequate training and limited technical proficiency among auditors. Organizational support, including leadership-driven initiatives, targeted training programs, and resource allocation, was found to significantly influence skill development, aligning with findings from Abdelwahed et al. (2024) and Iwuanyanwu et al. (2023). To bridge the skills gap, auditing firms must prioritize professional development through tailored training, mentorship, and fostering a culture of adaptability and innovation (Eziefule et al., 2022). Such initiatives not only enhance the competence of auditors in using AI tools but also contribute to improved audit quality and strategic decision-making (Han et al., 2023). By leveraging AI technologies effectively, organizations can remain competitive in the rapidly evolving digital landscape, ensuring sustainable growth and relevance in auditing practices (Adelakun, 2022). Future studies should examine the longitudinal effects of organizational support and training interventions across diverse auditing contexts.

VII. Implications

This study offers key implications for addressing the skills gap in AI-driven IT auditing in Nigeria. The findings highlight the pivotal role of organizational support in bridging this gap, emphasizing the importance of investments in tailored training and resource allocation to build auditors' proficiency. This aligns with the Institute of Chartered Accountants of Nigeria's (ICAN) goals of advancing audit practices through capacity building. Moreover, the insights into perceived usefulness and ease of use highlight the need for intuitive AI-driven tools and hands-on training to enhance accessibility, especially for small and medium-sized audit firms. By addressing barriers such as cost and technical expertise, these firms can harness AI to improve efficiency and accuracy in auditing practices. Additionally, the study provides a framework for policymakers, professional bodies, and software providers to establish incentives and support systems that encourage AI adoption. Public awareness campaigns are also crucial to inform audit firms of the strategic benefits of AI tools. Finally, this research contributes to the growing body of literature on AI-enabled auditing, offering actionable insights for fostering innovation and ensuring the Nigerian auditing sector remains competitive and aligned with global technological advancements.

VIII. Limitations

This study, while providing valuable insights into the skills gap in AI-driven IT auditing within Nigeria, has several limitations. The reliance on self-reported data through structured questionnaires may introduce response bias, as participants might overstate their familiarity with AI tools or the level of organizational support to present favorable perceptions. Additionally, the sample size, although sufficient for statistical analysis, may not fully reflect the diversity of auditing practices across Nigeria, particularly among smaller firms in less urbanized areas. The focus on specific factors such as perceived usefulness, ease of use, and organizational support excludes other potential influences, such as regulatory constraints, economic challenges, and cultural attitudes, which may also significantly impact the adoption of AI-driven auditing tools. Furthermore, the study's findings are contextualized within Nigeria, limiting their generalizability to markets with different economic, technological, and regulatory environments. The cross-sectional nature of the study also restricts its ability to examine the evolution of perceptions and skills over time. Future research should consider longitudinal studies, larger and more diverse samples, and mixed-method approaches to validate and expand on these findings. Despite these limitations, the study offers a crucial foundation for addressing the identified skills gap and advancing the adoption of AI-driven tools in Nigerian auditing.

References

[1] Abdelwahed, A. S., Abu-Musa, A. A., Moubarak, H., & Badawy, H. A. (2024). The use of big data and analytics in external auditing: Does audit firm size matter? Evidence from a developing country. *South African Journal of Accounting Research*, *38*(2), 113-145.

[2] Abiola, J.O. (2014), "*The impact of information and communication technology on internal auditors' independence: a PEST Analysis of Nigeria*", Journal of Scientific Research and Reports, Vol. 3 No. 13, pp. 1738-1752.

[3] Abou-El-Sood, H., Kotb, A. and Allam, A. (2015), "*Exploring auditors' perceptions of the usage and importance of audit information technology*", International Journal of Auditing, Vol. 19 No. 3, pp. 252-266.

[4] Abu Huson, Y., Sierra-García, L., & Garcia-Benau, M. A. (2024). A bibliometric review of information technology, artificial intelligence, and blockchain on auditing. *Total Quality Management & Business Excellence*, *35*(1-2), 91-113.

[5] Adelakun, B. O. (2022). Ethical Considerations in the Use of AI for Auditing: Balancing Innovation and Integrity. *European Journal of Accounting, Auditing and Finance Research*, *10*(12), 91-108.

[6] Adeyemi, S.B., Mohammed, A.K., Ogundeji, M.G. and Oladipupo, M.T. (2014), "*Audit technology tools and business process assurance: assessment of auditors' perspective in Nigeria*", Universal Journal of Industrial and Business Management, Vol. 2 No. 4, pp. 93-102.

[7] Adigwe, C. S., Olaniyi, O. O., Olabanji, S. O., Okunleye, O. J., Mayeke, N. R., & Ajayi, S. A. (2024). Forecasting the future: The interplay of artificial intelligence, innovation, and competitiveness and its effect on the global economy. *Asian journal of economics, business and accounting*, *24*(4), 126-146.

[8] Afsay, A., Tahriri, A., & Rezaee, Z. (2023). A meta-analysis of factors affecting acceptance of information technology in auditing. *International Journal of Accounting Information Systems*, *49*, 100608.

[9] Anomah, S., Ayeboafo, B., Owusu, A., & Aduamoah, M. (2024). Adapting to AI: exploring the implications of AI integration in shaping the accounting and auditing profession for developing economies. *EDPACS*, *69*(11), 28-52.

[10] Betti, N. and Sarens, G. (2021), "*Understanding the internal audit function in a digitalised business environment*", Journal of Accounting and Organizational Change, Vol. 17 No. 2, pp. 197-216.

[11] Byrne, B.M. (2013), 'Structural Equation Modeling with EQS: Basic Concepts', Applications, and Programming, Routledge, Lawrence Erlbaum Associates, New York, London.

[12] Celestin, M., & Vanitha, N. (2019). Digital transformation and the audit process: How tech is changing auditor roles. *International Journal of Applied and Advanced Scientific Research*, *4*(2), 49-55.

[13] CGMA, C. (2018). Blockchain augmented audit–benefits and challenges for accounting professionals. *The journal of theoretical accounting research*, *14*(1), 117-137.
[14] Chopra, K. (2019), "*Indian shopper motivation to use artificial intelligence: generating Vroom's expectancy theory of motivation using grounded theory approach*", International Journal of Retail and Distribution Management, Vol. 47 No. 3, pp. 331-347.
[15] Correia, T., Pedrosa, I. and Costa, C.J. (2019), "Open source software in financial auditing", Organizational Auditing and Assurance in the Digital Age, IGI Global, pp. 188-202.
[16] Damerji, H. and Salimi, A. (2021), "*Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting*", Accounting Education, Vol. 30 No. 2, pp. 107-130.
[17] DeLone, W.H. and McLean, E.R. (2003), "*The DeLone and McLean model of information systems success: a ten-year update*", Journal of Management Information Systems, Vol. 19 No. 4, pp. 9-30.
[18] Eziefule, A. O., Adelakun, B. O., Okoye, I. N., & Attieku, J. S. (2022). The Role of AI in Automating Routine Accounting Tasks: Efficiency Gains and Workforce Implications. *European Journal of Accounting, Auditing and Finance Research*, *10*(12), 109-134.
[19] George, D. and Mallery, M. (2003), "*Using SPSS for Windows step by step: a simple guide and reference*".
[20] Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R. L. (2006), Multivariate Data Analysis, 6th ed., Pearson Prentice Hall, New Jersey.
[21] Han, H., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial Intelligence: A literature review. *International Journal of Accounting Information Systems*, *48*, 100598.
[22] Iwuanyanwu, U., Apeh, A. J., Adaramodu, O. R., Okeleke, E. C., & Fakeyede, O. G. (2023). Analyzing the role of artificial intelligence in it audit: current practices and future prospects. *Computer Science & IT Research Journal*, *4*(2), 54-68.
[23] Kim, H.J., Kotb, A. and Eldaly, M.K. (2016), "*The use of generalized audit software by Egyptian external auditors: the effect of audit software features*", Journal of Applied Accounting Research, Vol. 17 No. 4, pp. 456-478.
[24] Lennox, C., & Pittman, J. (2010). Auditing the auditors: Evidence on the recent reforms to the external monitoring of audit firms. *Journal of accounting and economics*, *49*(1-2), 84-103.
[25] Mahzan, N. and Lymer, A. (2014), "*Examining the adoption of computer-assisted audit tools and techniques: cases of generalized audit software use by internal auditors*", Managerial Auditing Journal, Vol. 29 No. 4, pp. 327-349.
[26] Mansour, E.M. (2016), "*Factors affecting the adoption of computer assisted audit techniques in audit process: findings from Jordan*", Business and Economic Research, Vol. 6 No. 1, pp. 248-271.
[27] Omoteso, K. (2016), Audit Effectiveness: Meeting the IT Challenge, Routledge, New York.
[28] Oni, A.A. (2015), "*Computer assisted audit techniques and audit quality in developing countries: evidence from Nigeria*", Journal of Internet Banking and Commerce, Vol. 20 No. 2, pp. 1-17.
[29] Onwubuariri, E. R., Adelakun, B. O., Olaiya, O. P., & Ziorklui, J. E. K. (2024). AI-Driven risk assessment: Revolutionizing audit planning and execution. *Finance & Accounting Research Journal*, *6*(6), 1069-1090.
[30] Pallant, Y. (2001), SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS for Windows, 3rd ed., McGraw Hill Open University Press, Maidenhead, Berkshire.
[31] Payne, E.A. and Curtis, M.B. (2016), "*Factors associated with auditors' intention to train on optional technology*", Current Issues in Auditing, Vol. 11 No. 1, pp. A1-A21.
[32] Smidt, L., Steenkamp, L., Ahmi, A., van der Nest, D.P. and Lubbe, D.S. (2021), "*Assessment of the purpose of the use of GAS: a perspective of internal audit functions in Australia*", International Journal of Information Systems in the Service Sector (IJISSS), Vol. 13 No. 2, pp. 65-82.
[33] Tijani, O.M. (2014), "*Built-in functions and features of data analysis software: Predictors of optimal deployment for continuous audit assurance*", Scholars Journal of Economics, Business and Management, Vol. 1 No. 1, pp. 7-18.
[34] Venkatesh, V. and Bala, H. (2008), "*Technology acceptance model 3 and a research agenda on interventions*", Decision Sciences, Vol. 39 No. 2, pp. 273-315.
[35] Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "*User acceptance of information technology: toward a unified view*", MIS Quarterly, pp. 425-478.

Appendix 1 – Research Questionnaire

Instructions:

This survey is designed to collect data for academic purposes. Your responses will be kept confidential and used solely for this research. Please read each statement carefully and select the option that best reflects your opinion or experience.

Section A: Demographic Information

1. What is your age?
o 18–25
o 26–35
o 36–45
o 46 and above
2. What is your highest level of education?
o Diploma
o Bachelor's Degree
o Master's Degree
o Others
3. What is your job role?
o Internal Auditor
o External Auditor
o Accountant
o Other Finance Roles
4. How many years of auditing experience do you have?
o Less than 2 years
o 2–5 years
o 6–10 years
o Over 10 years
5. What type of organization do you work for?
o Small Audit Firm
o Medium-Sized Audit Firm
o Big 4 Firm
o Freelance/Independent

Section B: Awareness and Perceived Usefulness of IT Auditing Tools

Rate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree):

1. I am aware of the existence of IT auditing tools and their applications.
2. IT auditing tools improve the efficiency of audit tasks.
3. These tools enhance the accuracy of identifying anomalies and risk factors.
4. The use of IT auditing tools reduces the time required to complete audits.
5. Implementing IT tools significantly improves overall audit quality.

Section C: Perceived Ease of Use of AI-Driven Auditing Technologies

Rate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree):

1. AI-driven auditing tools are easy to learn and use.
2. The interface of these tools is intuitive and user-friendly.
3. I feel confident in using AI tools with adequate training.
4. AI technologies simplify complex auditing tasks.
5. The time required to understand these tools is reasonable.

Section D: Organisational Support for Advanced Tools Adoption

Rate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree):

1. My organisation actively supports training in IT and AI auditing.
2. Leadership encourages the adoption of advanced auditing tools.
3. Adequate resources are allocated for implementing IT auditing technologies.
4. Technical support is readily available for using these tools in auditing.
5. My organisation promotes innovation and adaptability to new technologies.