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ORIGINAL

Individual and Technological Factors Affecting the Adoption of AI-Powered Remote Auditing in the Jordanian Banking Sector

Factores individuales y tecnológicos que afectan la adopción de auditoría remota impulsada por IA en el sector bancario jordano

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ABSTRACT

Introduction: artificial intelligence technologies have recently contributed to the field of remote auditing and have led to significant improvements in the efficiency and outcomes of the audit process. However, this professional technological integration remains unexplored in the Jordanian banking sector. Accordingly, understanding the mechanism of integration between these factors is essential to keep pace with the evolving work environment. This study aims to examine how these factors affect the adoption of remote auditing supported by artificial intelligence in Jordanian banks.
Method: a quantitative approach consistent with a cross-sectional design was used to collect primary research data. A structured questionnaire was distributed to 158 decision-makers in various commercial banks in Jordan. The questionnaire measured individual factors (e.g., skill level of users and Attitude towards technology) and technological factors (e.g., technology readiness, data security and privacy, and integration capabilities). Structural equation modeling (SEM) was used to test the relationships between these factors and intention to adopt AI-powered remote auditing using SMART PLS.
Results: the results depicted that all factors, including individual and technological factors, significantly influenced the adoption of AI-powered remote auditing. Attitude towards technology and integration capabilities were the strongest predictors. Additionally, technology readiness, data security and privacy, and skill level of users had moderate but significant, effects on adoption intention.
Conclusion: the findings emphasize that both individual perceptions and technological robustness are crucial for adopting AI-powered remote auditing in Jordanian banks. Improving system reliability and showcasing the benefits of AI tools can significantly boost adoption rates.

Keywords: AI-Powered Remote Auditing; Technology Readiness; Data Security and Privacy; Integration Capabilities; Auditor Skill Level; Attitude Towards Technology.

RESUMEN

Introducción: las tecnologías de inteligencia artificial han contribuido recientemente al campo de la auditoría remota y han llevado a mejoras significativas en la eficiencia y los resultados del proceso de auditoría. Sin embargo, esta integración tecnológica profesional sigue siendo inexplorada en el sector bancario de Jordania. Por lo tanto, comprender el mecanismo de integración entre estos factores es esencial para mantenerse al día con el entorno laboral en evolución. Este estudio tiene como objetivo examinar cómo estos factores afectan la adopción de la auditoría remota respaldada por inteligencia artificial en los bancos jordanos.
Método: se utilizó un enfoque cuantitativo coherente con un diseño transversal para recopilar datos primarios de investigación. Se distribuyó un cuestionario estructurado a 158 responsables de la toma de decisiones en varios bancos comerciales de Jordania. El cuestionario midió factores individuales (por ejemplo, el nivel de habilidad de los usuarios y la actitud hacia la tecnología) y factores tecnológicos (como la preparación tecnológica, la seguridad y privacidad de los datos, y las capacidades de integración). Se utilizó el modelado de ecuaciones estructurales (SEM) para probar las relaciones entre estos factores y la intención de adoptar la auditoría remota impulsada por inteligencia artificial, utilizando SMART PLS.
Resultados: los resultados mostraron que todos los factores, tanto individuales como tecnológicos, influyeron significativamente en la adopción de la auditoría remota impulsada por inteligencia artificial. La actitud hacia la tecnología y las capacidades de integración fueron los predictores más fuertes. Además, la preparación tecnológica, la seguridad y privacidad de los datos, y el nivel de habilidad de los usuarios tuvieron efectos moderados pero significativos en la intención de adopción.
Conclusiones: los resultados destacan que tanto las percepciones individuales como la solidez tecnológica son fundamentales para la adopción de la auditoría remota impulsada por inteligencia artificial en los bancos jordanos. Mejorar la fiabilidad del sistema y demostrar los beneficios de las herramientas de IA puede aumentar significativamente las tasas de adopción.

Palabras clave: Auditoría Remota Impulsada por IA; Preparación Tecnológica; Seguridad y Privacidad de los Datos; Capacidades de Integración; Nivel de Habilidad del Auditor; Actitud Hacia la Tecnología.

INTRODUCTION

Artificial intelligence is a general term that includes methods used in simulating human intelligence through modern technologies such as computer systems, where these systems become capable of performing tasks that require human intelligence, such as learning, solving problems, making decisions, etc.[1] In recent years, artificial intelligence technologies have developed rapidly and have affected various sectors, including the audit sector, where artificial intelligence tools have proliferated and contributed to a gradual shift from traditional auditing to remote auditing. Remote auditing is based on the procedures followed to verify the accuracy of data using digital tools.[2] The integration of artificial intelligence into these remote auditing methods has enhanced efficiency, accuracy, and decision-making capabilities.[3]

The rise of artificial intelligence globally is having a big impact on the financial sector, mainly in auditing practices. A report by PwC shows that AI could contribute around $15,7 trillion to the global by 2030.[4] Many sectors, banking included, are embracing AI to improve operation efficiency. For auditing, AI tools help speed up data analysis, detect fraud and ensure compliance - all critical in our fast-digitizing financial landscape.[5,6] The gradual integration of AI across multiple industries is seen in Jordan and many other countries, most notably banking. However, despite these developments, remote AI-based auditing remains limited in Jordan's banks.[7]

The reasons for the adoption gap boil down to several factors. These include fears about data security, technological readiness, and user skill levels in handling complex artificial intelligence tools.[8,9] While it's evident AI holds benefits in auditing, individual and technological variables are pivotal in determining whether banks effectively adopt AI-based solutions.[10] Globally, cybersecurity and technological infrastructure are identified as major challenges in AI adoption.[11,12] As per a 2023 McKinsey report, up to 64 % of global organisations cited security concerns as an obstacle to fully leveraging AI.[13] In Jordan, the banking sector faces similar issues. These are compounded by the need to improve the alignment between user attitudes towards technology and the capabilities of AI systems. Addressing these concerns is of the utmost importance for banks looking to maintain their competitive edge in an increasingly digital financial landscape.

This study strives to grasp how individual and technological influences shape the adoption of AI-backed remote auditing in Jordan's banking sector. By gauging key factors driving this adoption, the research offers practical insights that can steer formulation of strategies to strengthen AI integration in auditing practices. Moreover, the study's purpose is to assess how influences such as user skills, attitudes toward technology, system reliability, data security, and integration abilities affect one's intention to adopt AI-supported remote

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auditing. This understanding should lend a helping hand to banks and tech suppliers to comprehend efficiently what conditions are necessary for successfully executing AI.

Literature review and hypotheses development

Need for AI-remote auditing system adoption in the banking sector

The banking industry is changing quickly, and it is now essential to implement AI-powered remote auditing tools. Conventional auditing techniques are frequently labor-intensive, resource-intensive, and prone to human mistake. Through the effective integration of artificial intelligence into auditing procedures, banks can achieve operational efficiency, improve precision, and efficiently manage risks. Large volumes of financial data can be analyzed in real-time by AI algorithms, which can then spot anomalies or questionable activity with previously unheard-of efficiency. Furthermore, banks may do audits remotely thanks to remote auditing solutions, which eliminates the requirement for in-person attendance and the related expenses. The adoption of AI-driven remote auditing systems not only enhances regulatory compliance but also strengthens the overall security posture of financial institutions, assuring trust and confidence among stakeholders in an era characterized by digital transformation and growing cybersecurity threats.

Technological factors

Technology readiness

The adoption of AI-powered auditing solutions is heavily influenced by the organization's current IT infrastructure and technology readiness. Businesses that have reached a higher level of digital maturity and IT sophistication will find it easier to incorporate and apply AI technologies. There is ample evidence to support the effectiveness of AI in data analysis for auditing purposes. Al Shbail et al. (2024), for instance, describe how machine learning models are transforming risk assessment in audits by identifying patterns in data that human auditors were previously unable to identify. As a result, the following theory was developed.(14)

H1: The intention to adopt AI-powered auditing tools is positively impacted by technology readiness.

Data security and privacy

Concerns about privacy and data security are crucial when implementing AI-powered remote audits. Gaining the trust of users and stakeholders requires AI systems to adhere to relevant legislation and norms. Technologies like blockchain help to overcome the data security concerns in remote auditing. Blockchain offers a decentralized, secure structure that is perfect for the integrity and confidentiality requirements of audit data, as mentioned by Al Shbail et al. (2023). As a result, the following theory was developed.(15)

H2: The intention to adopt AI-powered auditing tools is positively impacted by data security and privacy.

Integration capabilities

It is essential that AI solutions be simple to integrate with current accounting and auditing software. Organizations can take use of AI capabilities with seamless integration without having to change current workflows. Khatatbeh et al. (2023) emphasizes the significance of integration capabilities by explaining that the use of AI tools in auditing is more seamless when these tools are compatible with the current financial software that organizations use. As a result, the following theory was developed.(16)

H3: The intention to adopt AI-powered auditing tools is positively impacted by integration capabilities.

Individual factors

Skill level of users

The acceptance of AI technology is influenced by the proficiency of auditors and other end users in its utilization. To fully utilize the technology, training and ongoing education on artificial intelligence (AI) and its applications in auditing are essential. The topic of the talent gap is crucial when it comes to the deployment of AI in auditing. Al Shbail et al. (2024) stress the importance of specialized training courses to equip auditors ready for the AI-driven technology revolution. As a result, the following theory was developed.(14)

H4: The intention to adopt AI-powered auditing tools is positively impacted by skills level of auditors.

Attitude towards technology

Individual perspectives on technology and receptivity to change have a big impact on adoption as well. AI-driven auditing solutions are more likely to be adopted by users who are more tech-savvy and receptive to new tools. Jaradat et al. (2022) investigates the role of individual attitudes on technology adoption by surveying auditors' preparedness and desire to interact with AI technologies.(17) The survey highlights conflicting emotions driven by worries of losing one's job. As a result, the following theory was developed;

H5: The intention to adopt AI-powered auditing tools is positively impacted by attitude towards technology.

METHOD

Data design and collection

To acquire an effective statistical data inspection, this study employed a quantitative approach, chosen for its time and cost efficiency. A survey was recommended, taking into account the study's goals, available data, and budget constraints. The study community comprised of top executives in Jordanian banks. it is a distinct population of decision-makers directly involved in the adoption of technological innovations. This encompassed branch managers, chief executives, financial directors, operations managers, risk managers, technology managers, human resources managers, and marketing managers.

Participants were specially selected using purposeful sampling.[18] The study aimed at experienced executive directors who have the ability to adopt remote auditing supported by artificial intelligence. Participants were required to have a minimum of five years experience in relevant roles and play a part in making strategic decisions for their organizations. Beginners or employees not engaged with technology or auditing processes were excluded, ensuring high-level decision-makers with knowledge of AI and auditing were included. The survey was designed with structured questions measuring individual factors such as user skill level and attitudes towards technology. Technological factors such as technology readiness, data security, and integration abilities were also addressed.[19] Variables were processed through a Likert scale to evaluate perceptions and intentions about adopting AI-supported remote auditing.

Before data collection, participants were made aware of the study's intent. Each participant provided consent. Every ethical aspect was considered, including protecting anonymity and voluntary character of participation. The study received ethical agreement from the relevant research committee. Out of 200 disseminated surveys, 158 valid responses were collected, yielding a response rate of 79 %. Therein these responses were deemed sufficient for examination using Partial Least Squares Structural Equation ModellingPLS-SEM). It enabled a systematic investigation into variable relationships and reliable execution of results.

Common method bias

One issue with common method bias (CMB) is that a cross-sectional design, which is more likely when data collection is done largely in cross-sectional settings. For this reason, investigating the CMB problem is essential. We carried out a thorough collinearity examination using the variance inflation factor (VIF).[20] All of the VIF values were below the 3,3 threshold, according to the results (see table 1). The findings demonstrated that CMB was not an issue for this investigation.

RESULTS

Using SmartPLS version 4, partial least squares structural equation modeling (PLS-SEM) was used to examine the data in order to test the suggested relationships. For handling complex research models such as the one we have here, PLS-SEM is a dependable and well-liked technique.[21] Odat et al. (2023) noted that PLS-SEM was selected in part due to its exploratory predictive nature, which aligns with the objectives of our investigation.[22] Two models are usually used in SEM: an exterior model and an inner model. According to Jarahat et al. (2023), the external model is also referred to as things, manifestations, or measuring models, whereas the internal model is also called a structural model.[23] The external model shows the links between the items and the constructs, whereas the inner model shows the relationship between independent variables (IV) and dependent variables (DV).[24]

Measurement model

Since all of the component was reflecting, the model was first validated in order to assess the outer model. As per Hair et al. (2019), evaluating the validity of measurements is necessary, encompassing both the construct level and the individual item level (indicator reliability). (reliability of internal consistency). Furthermore, an assessment was conducted on both discriminant and convergent validity.[25]

To assess indicator reliability—that is, the proportion of each indicator's variation explained by the construct, which ought to be at least 50 %—indicator loadings must to be tracked.[26,27] It is recommended that indicator loadings be more than or equal to 0,708 (see table 1) since this value indicates that the construct explains 50 % of the indicator variation.[28] Table 1 shows that all indicator loadings were greater than 0,708, indicating adequate indication dependability. In contrast, the internal consistency reliability was examined using the composite reliability (CR) and Dijkstra and Henseler's rho_A.[29] Table 1 shows that for every structure, the CR was higher than 0,7.[30] The rho_A was also more than 0,7 in each case.[31] As a result, the internal consistency dependability of the suggested outer model was good.

Discriminant validity is ensured by adhering to the Heterotrait Monotrait (HTMT) requirements, which specify that HTMT values should be less than 0,90 as recommended by Henseler, Ringle, and Sarstedt (2015).[32] Nonetheless, other authors contend that HTMT values less than 0,85 are preferable, in keeping with Hair, Howard, and Nitzl (2020). Table 2 shows that the intention to employ AI-powered auditing tools, user skill level, data security and privacy, integration capabilities, and technology readiness all have HTMT values less than 0,85. Thus, discriminant validity is regarded as established.[24]

Table 1. Construct Reliability and Validity

Construct	Code	Loadings	VIF	C. alpha	rho_A	CR	AVE
Technology readiness	TR.1	0,808	1,230	*0,838*	*0,809*	*0,781*	*0,569*
TR.2	0,869	1,206					
TR.3	0,733	1,065					
Data security and privacy	DSP.1	0,726	1,219	0,867	0,884	0,836	0,684
DSP.2	0,804	1,133					
DSP.3	0,859	1,067					
Integration capabilities	IC.1	0,839	1,101	0,873	0,865	0,851	0,663
IC.2	0,828	1,031					
IC.3	0,726	1,132					
Skill level of users	SLU.1	0,887	1,148	0,751	0,746	0,841	0,638
SLU.2	0,866	1,469					
SLU.3	0,747	1,420					
Attitude towards technology	ATT.1	0,786	1,369	0,725	0,783	0,840	0,632
ATT.2	0,836	1,393					
ATT.3	0,856	1,595					
Intention to adopt AI-powered auditing tools	AI-P.1	0,866	1,389	0,727	0,734	0,846	0,649
AI-P.2	0,784	1,494					
AI-P.3	0,833	1,891					
AI-P.4	0,840	1,395					

Table 2. Discriminant validity-HTMT criterion

Construct	1	2	3	4	5	6
Intention to adopt AI-powered auditing tools	-					
Attitude towards technology	0,388	-				
Data security and privacy	0,293	0,422	-			
Integration capabilities	0,657	0,126	0,425	-		
Skill level of users	0,426	0,264	0,693	0,472	-	
Technology readiness	0,727	0,377	0,638	0,520	0,735	-

Assessment of the structural (inner) model

In order to validate the inner model and the suggested hypotheses, a structural model assessment was carried out in this work. First, technical readiness, data security and privacy, integration capabilities, user skill level, and attitude toward technology explained 68,9 % of the variance in intention to utilize AI-powered auditing tools (R2 = 0,689). This indicates that the predictors had a moderate impact on the variance in the intention to use auditing tools driven by artificial intelligence. Furthermore, because the Q2 value of 0,273 is greater than zero, it also indicates the predictive validity of the model.[19] f2 was used as the effect size metric in accordance with Cohen's (1998) recommendations. Table 3 illustrates that while user skill level and data security and privacy have a minor impact on the intention to employ AI-powered auditing tools, technological readiness, integration capabilities, and attitude toward technology have a moderate effect.

Table 3. Structural model results

Construct	R^2	Adj. R^2	f^2	Q^2
Technology readiness	-	-	0,281	-
Data security and privacy	-	-	0,105	-
Integration capabilities	-	-	0,297	-
Skill level of users	-	-	0,096	-
Attitude towards technology	-	-	0,311	-
Intention to adopt AI-powered auditing tools	0,689	0,678	-	0,273

A bootstrapping approach with 10,000 iterations was used to test hypotheses and assess the significance of the route coefficients of the structural linkages. The results presented in Table 4 demonstrate that auditors' intention to adopt AI-powered auditing tools was significantly influenced by factors such as technology readiness, data security and privacy, integration capabilities, user skill level, and attitude toward technology (β = 0,314, 0,132, 0,358, 0,112, and 0,391: p < 0,05, respectively). As a result, the following hypotheses were confirmed: hypothesis 1, hypothesis 2, hypothesis 3, hypothesis 4, and hypothesis 5. Table 4 provides a summary of the hypothesis testing results.

Table 4. Hypotheses testing

Structural path	Coef (*B*) and (T Statistics)	Bias-corrected 95 % CI Lower Upper	Remarks
H1: Technology readiness -> Intention to adopt AI-powered auditing tools	0,314 (2,988)	(0,169, 0571)	Supported
H2: Data security and privacy -> Intention to adopt AI-powered auditing tools	0,132 (2,105)	(0,085, 0,418)	Supported
H3: Integration capabilities -> Intention to adopt AI-powered auditing tools	0,358 (3,017)	(0,183, 0,608)	Supported
H4: Skill level of users -> Intention to adopt AI-powered auditing tools	0,112 (2,004)	(0,047, 0,426)	Supported
H5: Attitude towards technology -> Intention to adopt AI-powered auditing tools	0,391 (3,473)	(0,201, 0,722)	Supported

DISCUSSION

Creating a model for the variables influencing Jordanian commercial banks' adoption of AI-powered remote auditing was the study's main objective. The paper states that technical maturity, data security and privacy, integration capabilities, auditor skill level, and attitude toward technology all have a major impact on the adoption of AI-Powered remote auditing. The study's findings are expected to aid Jordanian commercial banks in implementing remote auditing, and the adoption variables that were identified will increase awareness of AI-Powered remote audit adoption among bank owners and investors. These results would also assist bank management in focusing on the elements that would promote the adoption of AI-Powered remote auditing.

The current study looked at the effects of the major factors influencing the adoption of AI-Powered remote auditing rather than analyzing the effects of every possible element. Future studies should examine other variables and the degree to which they impact people's acceptance of remote auditing powered by artificial intelligence. Because the study's environment consisted of Jordanian commercial banks, the conclusions might not be applicable to just any other developing nation. Furthermore, even if the study's data quality is suitable for exploratory research, the data collection process was dependent on the respondents' perceptions, experiences, and understanding, which may not represent an objective perception. Not to mention, the sample size selected was rather small; therefore, the constructs can be studied in a larger and more general sample in future research.

CONCLUSIONS

The chief purpose of this study was to construct a model outlining key variables that weigh significantly on the adoption of AI-assisted remote auditing in Jordanian commercial banks. The results spotlight how such factors are instrumental in the adoption of AI-assisted remote auditing. These findings provide valuable guidance for bank management to concentrate on the most critical factors that would aid the adoption of AI-assisted remote auditing. However, the research did not address all potential influencing factors. Future studies ought to explore other variables and assess their effect on the uptake of AI-assisted remote auditing. Furthermore, data collection rested on respondent perceptions and experiences, which may lack full objectivity. It suggests future research could benefit from a larger, more diverse sample for more validation of results and generalization.

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