The Adoption Factors and Effects of Digital Technologies on Auditors' Performance in Sub-Saharan Africa

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Abstract

This paper examines the factors driving the adoption of digital technologies and their impact on auditors' performance. It empirically validates a research model grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Action and Transformation Control (TACT). The study involved 120 auditors (seniors, managers, and senior managers) from audit firms within the OHADA region and employed Partial Least Squares Structural Equation Modeling (PLS-SEM).

The findings reveal that expected performance, expected effort, and facilitating conditions are key determinants of digital technology adoption among auditors. Moreover, the adoption of these technologies significantly enhances auditors' performance, particularly in fostering innovative performance. These results provide a novel contribution to audit literature by being the first to integrate UTAUT and TACT in this context, offering insights into adoption factors and performance dimensions.

Keywords: digital technologies, adoption factors, performance, external auditors, PLS-SEM

1. Introduction

The technological boom reshaping the business world is transforming how companies and their governance bodies manage and oversee their activities. Known as the "digital age," this era is characterized by unprecedented technological innovations that significantly impact all activities related to information exchange. This transformation extends to the auditing profession (Henry & Rafique, 2021; Taşar & ErkuŞ, 2022) and accounting (Mohd Noor et al., 2022), introducing various forms of digital transformation such as cognitive technologies like artificial intelligence (AI) (Al-Sayyed, Al-Aroud, & Zayed, 2021; Albawwat & Frijat, 2021;

Fedyk et al., 2022; Hasan, 2021; Henry & Rafique, 2021), blockchain technology (Abreu, Aparicio, & Costa, 2018; Atik Yildirim, 2021; Pugna & Duţescu, 2020; Schmitz & Leoni, 2019; Silva, Inácio, & Marques, 2022; Zemánková, 2019), smart contracts, and Big Data Analytics (Al-Ateeq et al., 2022; Chu & Yong, 2021). Each of the Big Four accounting firms invests over $250 million annually in these advancements (Albawwat & Frijat, 2021), driving the digitalization of audit processes to leverage big data and new tools for added client value (Manita et al., 2020). PwC has developed "GL.ai," an AI-powered tool that examines transactions to identify potential fraud or errors without bias, alongside other platforms like "Cash.ai" for automated cash audits and "Aura," a cloud-based global audit management system. Similarly, Deloitte's "Omnia DNAV" integrates cognitive technologies and data analytics, earning Deloitte multiple awards for innovation in audit practices, including the "Audit Innovation of the Year" for platforms like "Cortex" and "Argus" (Deloitte, 2017). KPMG's "Clara" enables efficient audits with advanced anomaly detection, while EY's "Canvas," "Helix," and "Blockchain Analyzer" enhance transparency and data analysis. Mazars employs "ATLAS" to automate audit tasks, reducing manual processes.

These innovations signify a broader evolution in the auditing field, where technologies eliminate traditional manual processes (Taşar & ErkuŞ, 2022), improve risk assessments (Üçoğlu, 2020), enable data integration (Albawwat & Frijat, 2021), and provide actionable insights from multiple data sources (Al-Sayyed, Al-Aroud, & Zayed, 2021). Predictions indicate that by 2025, 30% of audits will incorporate digital tools (Üçoğlu, 2020), with fully automated audit reports becoming standard (Abreu et al., 2018). In this connected world, the role of auditors is evolving beyond industry-specific expertise to include advanced digital skills for client data analysis and risk identification (Taşar &

ErkuŞ, 2022). Operating in an "up or out" system, auditors face increasing expectations for performance evaluations that now encompass technological capabilities (Goff, 2019). Auditors must adapt to this context to remain competitive (Mighiss & Kabbaj, 2021) and deliver high-value, technology-enabled audits (Deloitte, 2017; Tiberius & Hirth, 2019). While studies highlight how digital technologies transform auditing, few focus on their adoption and impact on performance. This chapter addresses this gap, exploring the factors driving the adoption of digital technologies by external auditors and evaluating their effects on performance, specifically within the OHADA region.

The research focuses on the following questions:

RQ1: What are the factors that determine the adoption of digital technologies by external auditors in the OHADA region

RQ2: What role do moderator variables such as gender, grade, and experience at the grade level play in the adoption of digital technologies by external auditors?

RQ3: What is the effect of adopting digital technologies on the performance of external auditors?

2. Hypotheses and Research Model

To address the raised issue, two theories are mobilized. These are the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Action Control and Transformation (TACT).

2.1 Research Hypotheses

The Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) serves as the foundation for analyzing the factors influencing auditors' adoption of digital technologies. This theory posits that expected performance, expected effort, social influence, and facilitating conditions are key determinants of technology adoption. Additionally, the Theory of Action Control and Transformation (TACT) is employed to examine the relationship between the adoption of digital technologies and auditors' performance.

2.1.1 Expected Performance (EP)

Expected performance, as defined by Venkatesh et al. (2003), refers to the extent to which individuals believe that using a system will enhance their work performance. This concept aligns with perceived usefulness in TAM (Davis, 1989), relative advantage in the Diffusion of Innovation Theory (Rogers, 1995), and intrinsic motivation (Davis, 1984). Within organizations, expected performance reflects employees' expectations of technological tools improving their job performance (Ling et al., 2012). Similarly, in individual contexts, as demonstrated by Matabishi (2019) in the DRC, greater performance expectations correlate with higher adoption likelihood. Studies by Brown et al. (2010) in Finland and Bader & Mohammad (2019) in Saudi Arabia corroborate that expected performance significantly influences the intention to adopt technology. Consequently, the following hypothesis is proposed:

• Hypothesis 1: Expected performance positively influences the adoption of digital technologies by external auditors.

2.1.2 Expected Effort (EE)

Expected effort refers to the degree of ease associated with using a system (Venkatesh et al., 2003). It corresponds to perceived ease of use in TAM, complexity in TDI, and complexity in MUPC. In technology adoption, expected effort reflects users' anticipation that the technology will be simple to operate (Brown, Dennis, & Venkatesh, 2010). Studies confirm that technologies requiring minimal effort are more likely to be adopted (Bader & Mohammad, 2019; Venkatesh et al., 2003). Similarly, Zhou, Lu, and Wang (2010) found that when users perceive technology as easy to use, they are more inclined to adopt it. Based on this, the following hypothesis is formulated:

• Hypothesis 2: Expected effort influences the adoption of digital technologies by external auditors.

2.1.3 Social Influence (SI)

Social influence, as defined by Venkatesh et al. (2003), is the extent to which an individual perceives that significant others believe they should use a technology. In this study, significant others include employers, colleagues, and friends working in other audit firms. Research by Ling et al. (2012) identified a significant positive impact of social influence on users' intention to adopt technology. This finding aligns with other studies confirming that social influence encourages employees to adopt information systems (Brown, Dennis, & Venkatesh, 2010; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Accordingly, the following hypothesis is proposed:

• Hypothesis 3: Social influence positively influences the adoption of digital technologies by external auditors.

2.1.4 Facilitating Conditions (FC)

Facilitating conditions refer to the extent to which individuals believe that an organizational and technical infrastructure is in place to support system use (Venkatesh et al., 2003). Studies by Ling et al. (2012) and Matabishi (2019) confirm that facilitating conditions positively influence employees' intention to adopt technologies. Other research also emphasizes their importance in technology adoption, particularly for new employees who require training on system usage (Bader & Mohammad, 2019; Ling et al., 2012). Organizations with a robust technical infrastructure are more likely to see employees adopting the technology (Venkatesh et al., 2003). Individual perceptions of control over technology use are shaped by the availability of resources that facilitate usage (Zhou, Lu, & Wang, 2010). Based on these findings, the following hypothesis is proposed:

• Hypothesis 4: Facilitating conditions positively influence the adoption of digital technologies by external auditors.

2.1.5 Digital Technology Adoption and Auditors' Performance

Auditors' performance is critical to ensuring the quality and integrity of audit services provided to clients (Louwers, Blay, & Sinason, 2018). They handle tasks such as risk assessment, planning, analytical reviews, and account verification, with their performance reliant on meeting deadlines and maintaining high-quality standards to fulfill firm objectives. Studies linking technology use to worker performance explore digital platforms' characteristics and their impact. For instance, Chung, Lee, and Kim (2014) demonstrate that habitual use and task-technology fit positively affect work performance.

In auditing, digital technologies like artificial intelligence (Al-Sayyed, Al-Aroud, & Zayed, 2021; Allouli & Boumeska, 2023; Fedyk et al., 2022; Hasan, 2021; Henry & Rafique, 2021; Zemánková, 2019), big data (Al-Ateeq et al., 2022; Chu & Yong, 2021; Cockcroft & Russell, 2018; Cristea, 2021), and blockchain (Abreu, Aparicio, & Costa, 2018; Atik Yildirim, 2021; Mione et al., 2020; Montes & Goertzel, 2019; Silva, Inácio, & Marques, 2022; Zemánková, 2019) have proven crucial for tasks such as audit planning, risk assessment, internal control evaluation, client acceptance, client relationship management, and fraud detection.

Allbabidi (2021) confirms these technologies significantly enhance operational efficiency, providing auditors with new competencies. Similarly, Al-Ansi (2015) emphasizes that information technology use enables auditors to improve performance. According to Duan, Deng, and Wibowo (2024), performance can be categorized as professional—completing tasks within assigned duties—and innovative—undertaking activities beyond standard requirements to achieve new results. Building on these insights, the following hypotheses are proposed:

• Hypothesis 8: Digital technology adoption has a positive effect on auditors' professional performance.

• Hypothesis 9: Digital technology adoption has a positive effect on auditors' innovative performance.

2.1.6 Control Variables

According to Venkatesh V. et al. (2003), there are variables that moderate the relationship between independent variables and technology adoption. These variables include age, gender, experience, and willingness. In this study, we considered gender, rank, and experience as moderating variables that could control the relationship between the independent variables and the variable of interest. Thus, the following hypotheses are derived:

• Hypothesis 5a: Gender moderates the influence of expected performance on the adoption of digital technologies by external auditors.

• Hypothesis 5b: Gender moderates the influence of expected effort on the adoption of digital technologies by external auditors.

• Hypothesis 5c: Gender moderates the relationship between social influence and the adoption of digital technologies by external auditors.

• Hypothesis 6a: Rank moderates the relationship between expected effort and the adoption of digital technologies by external auditors.

• Hypothesis 6b: Rank moderates the relationship between expected effort and social influence on the adoption of digital technologies by external auditors.

• Hypothesis 6c: Rank moderates the relationship between facilitating conditions and the adoption of digital technologies by external auditors.

• Hypothesis 7a: Experience at rank moderates the relationship between expected effort and the adoption of digital technologies by external auditors.

• Hypothesis 7b: Experience at rank moderates the relationship between social influence and the adoption of digital technologies by external auditors.

• Hypothesis 7c: Experience at rank moderates the relationship between facilitating conditions and the adoption of digital technologies by external auditors.

Based on the hypotheses formulated above, the proposed conceptual model can be conceptualized as follows.

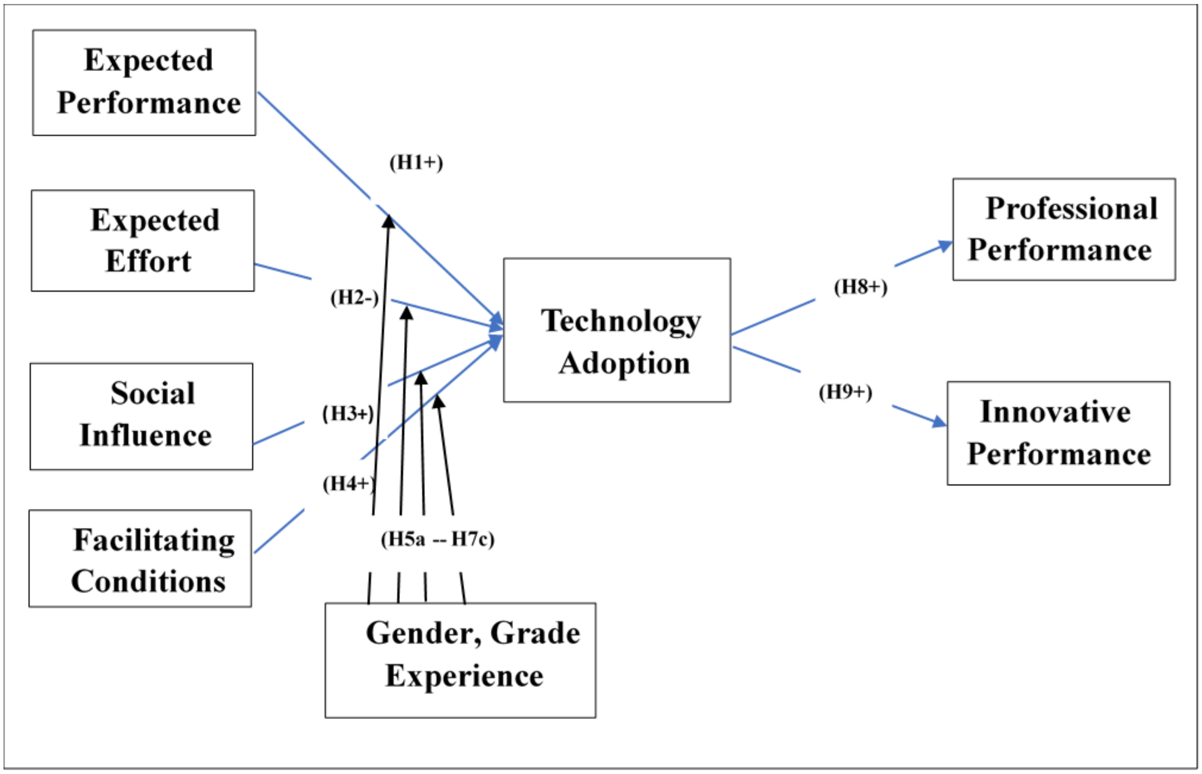

Figure 1. Conceptual Model

Source: Authors

3. Methodology

To test the formulated hypotheses, a research model based on a hypothetico-deductive approach was developed, relying on quantitative data. These data were collected through a questionnaire. The adopted methodology includes a detailed description of the constructs of the model, the methods used for data collection, the demographic profiles of the respondents, as well as the techniques employed for data analysis. All these aspects will be presented in detail to ensure a rigorous and transparent research approach.

3.1 Operationalization of Variables

To identify the attributes of digital technology adoption among auditors in the OHADA region, individual interviews were conducted with four auditors from MAZARS and KPMG. Each interview, lasting 15 minutes on average, explored the auditors' motivations, benefits, and challenges associated with digital technology. The aggregation unit, cited by at least two respondents, was retained (Evrard, Pras, & Roux, 2003). This led to the creation of 12 items, which were expanded with 35 additional items from the literature review. After a thorough analysis, including eliminating duplicates, excluding ambiguous items, and grouping similar ones, 8 items were removed, resulting in a refined set of 57 items. To measure the variables, a 7-point Likert scale was adopted, ranging from strongly disagree (1) to strongly agree (7) (Aissaoui & Abdelghaffar, 2021).

3.2 Data Collection and Sample

To determine the acceptable sample size for the population based on the conceptual model, we used non-probability sampling with the G*Power 3.1.9.7 software, considering the following parameters: a type I error rate of 0.05, and a medium effect size ($f^2 = 0.15$) (Hair Jr et al., 2021). Taking these parameters into account, the minimum sample size was set at 119 auditors. Data were collected between March and April 2024 using a Google form shared via social media (WhatsApp, LinkedIn) and email. The descriptive characteristics of the respondents are as follows: 120 auditors surveyed in the OHADA region, with the demographic characteristics presented in the following table:

Table 1. Demographic Characteristics

Description	**Désignation**	**Staff**	**%**
Gender	Woman	54	45.0
	Man	66	55.0
Grade	Senior	94	78.30%
	Manager	21	17.50%
	Senior manager	5	4.20%
Years of experiece at the grade	1 to 2 years	63	52.5%
	3 to 2 years	56	46.67%
	5 years and more	1	0.83%
Cabinet	AUDITEC	6	5.0%
	Deloitte	15	12.5%
	EXCO	14	11.7%
	EY	5	4.2%
	FCA	4	3.3%
	FIDECA	3	2.5%
	IDEA EXPERTISE	3	2.5%
	KPMG	11	9.2%
	Mazars	31	25.8%
	MGI STRONG	4	3.3%
	Moore Stephens	7	5.8%
	PWC	17	14.2%
Country	Benin	7	5.8
	Burkina Faso	5	4.2
	Cameroon	24	20.0
	Congo	6	5.0
	Ivory Coast	11	9.2
	Gabon	6	5.0
	Mali	8	6.7
	Niger	11	9.2
	DRC	16	13.3
	Senegal	22	18.3
	Tchad	1	0.8
	Togo	3	2.5
Total		120	100.0

Source: Authors

3.3 Data Analysis Method

To analyze the data, we employed Structural Equation Modeling based on Partial Least Squares (PLS-SEM), a method known for estimating complex models with multiple concepts, indicator variables, and structural paths, while handling non-normal data distributions (Hair et al., 2019). PLS-SEM is particularly useful for moderate sample sizes and exploratory or predictive research. Following Hair et al. (2019), this method is suited for studies aiming to test a theoretical framework from a predictive viewpoint and explore theoretical extensions in complex contexts. The analysis was conducted using SmartPLS software in two main steps.

The first step assessed the reliability and validity of the proposed model using indicators like Cronbach's alpha and Dillon-Goldstein's rho to measure internal consistency, with a reliability threshold of 0.7. The outer loadings of indicators had to exceed 0.7 for significance, and convergent validity was evaluated with the Average Variance Extracted (AVE), requiring a minimum value of 0.5.

The second step focused on the structural evaluation of variable relationships. The coefficient of determination (R^2) measured the variance explained by independent variables on dependent variables. Hypothesis significance was tested using bootstrapping with p-values to validate or reject structural relationships.

To examine moderating effects, Partial Least Squares Multigroup Analysis (PLS-MGA) was used to compare structural paths across different subgroups like age, gender, or type of university. PLS-MGA is flexible, not requiring strict assumptions on data distribution or variance homogeneity, making it ideal for moderate samples and non-normal data (Schuberth, Henseler, & Dijkstra, 2018). This analytical approach adheres to the methodological standards outlined by Hair et al. (2019).

4. Results of the Study

This section presents the results related to testing the proposed model to study the factors of adoption and the effects of digital technologies on auditors' performance.

4.1 Evaluation of the Measurement Model

To test the robustness of the proposed model, the reliability of the constructs and convergent validity were assessed using indicators such as: Outer loadings, Cronbach's Alpha, Composite reliability (rho_a), Composite Reliability (rho_c), and Average Variance Extracted (AVE), as recommended by Hair et al. (2019).

Table 2. Reliability of Constructs and Convergent Validity

	Items	**Outer loadings**	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Technology Adoption	TA1	0.735	0.839	0.85	0.886	0.61
	TA2	0.801				
	TA3	0.819				
	TA4	0.831				
	TA5	0.712				
Facilitating Conditions	FC1	0.765	0.871	0.881	0.912	0.722
	FC2	0.871				
	FC3	0.897				
	FC4	0.862				
Expected Effort	EE1	0.906	0.897	0.922	0.927	0.761
	EE2	0.892				
	EE3	0.850				
	EE4	0.839				
	SI2	0.887				

Social Influence	SI3	0.862	0.693	0.697	0.867	0.765
Expected Performance	EP1	0.670	0.854	0.865	0.892	0.581
	EP2	0.770				
	EP3	0.767				
	EP4	0.663				
	EP5	0.828				
	EP6	0.856				
Innovative Performance	IP1	0.812	0.951	0.97	0.96	0.802
	IP2	0.899				
	IP3	0.906				
	IP4	0.957				
	IP5	0.913				
	IP6	0.878				
Professional Performance	PP1	0.732	0.927	0.933	0.939	0.633
	PP3	0.836				
	PP4	0.854				
	PP5	0.830				
	PP6	0.696				
	PP7	0.886				
	PP8	0.848				
	PP9	0.691				
	PP10	0.762				

Source: Authors using Smart PLS 4.

The Fornell-Larcker criterion was used to verify discriminant validity, with the square root of the AVE needing to be higher than the shared variance between a construct and the other constructs. This means it should be higher than the correlation coefficients in the column.

Table 3. Discriminant Validity

	AT	FC	EE	SI	EP	IP	PP
AT	**0.781**						
FC	0.774	**0.850**					
EE	0.446	0.649	**0.872**				
SI	0.547	0.443	0.398	**0.874**			
EP	0.532	0.345	0.224	0.446	**0.762**		
IP	0.502	0.433	0.374	0.265	0.485	**0.895**	
PP	0.717	0.677	0.294	0.361	0.536	0.469	**0.796**

Source: Authors based on Smart PLS 4.

Another more conservative criterion is the heterotrait-monotrait (HTMT) ratio, which should be below 0.85. For this study, all values were below 0.85, and thus the HTMT was also checked, as can be seen.

Table 4. Heterotrait-Monotrait Ratio (HTMT) - Matrix

	AT	FC	EE	SI	EP	IP
AT						
FC	0.801					
EE	0.493	0.726				
SI	0.728	0.563	0.493			
EP	0.618	0.389	0.266	0.578		
IP	0.541	0.467	0.393	0.307	0.532	
PP	0.794	0.740	0.319	0.443	0.600	0.488

Source: Authors using Smart PLS 4.

TA = Technology Adoption, FC = Facilitating Conditions, EE = Expected Effort, SI = Social Influence, EP = Expected Performance, IP= Innovative Performance, PP = Professional Performance.e

The evaluation of the direction, strength, and significance level of the path coefficients (beta) are key elements in testing the research hypotheses of this study. The predictive relevance of the dependent variables, measured by "R^2", is considered. The value considered is the "adjusted" R^2, as it truly represents the level of explanation of the dependent variable by the explanatory variables. The minimum level for an individual R^2 should be greater than an acceptable minimum value of 0.10, i.e., 10% (Hair J. et al., 2013, 2017).

Table 5. Adjusted R-Squared

Dependent Variables	R-square	R-square adjusted
AT	0.761	0.723
IP	0.253	0.246
PP	0.513	0.509

Source: Authors based on Smart PLS 4.

In light of the table below, it should be noted that all endogenous variables have been explained by more than 24%. The variable "digital technology adoption" is explained by 72.3% (R2 equal to 0.723) by the 4 UTAUT variables (expected performance, expected effort, social influence, and facilitating conditions). The variable "auditor's professional performance" is explained by 50.9% (R2 equal to 0.509) by digital technology adoption. Finally, "innovative performance" is explained by 24.6% (R2 equal to 0.246) by digital technology adoption, as demonstrated by the structural equation model estimation.

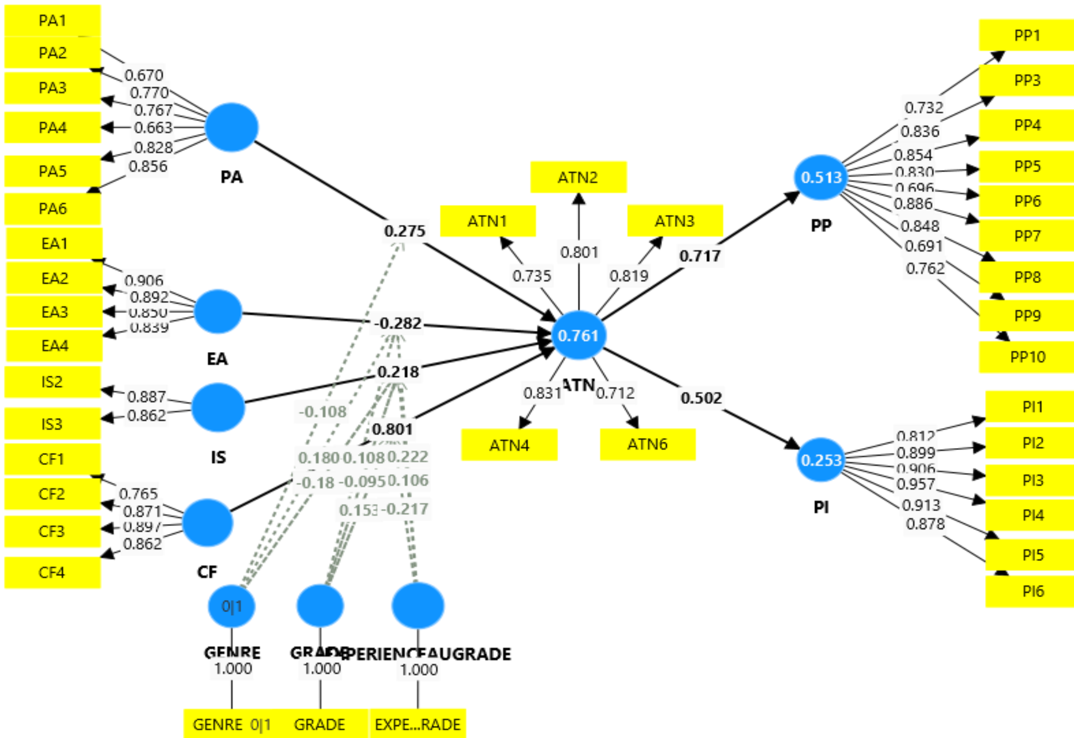

Figure 2. Testing the conceptual model through structural equations

Source: Authors based on Smart PLS 4.

TA = Technology Adoption, FC = Facilitating Conditions, EE = Expected Effort, SI = Social Influence, EP = Expected Performance, I= Innovative Performance, PP = Professional Performance.

4.2 Hypothesis Testing

To evaluate the hypotheses, the T-statistic was used as the criterion. According to the recommendations of Hair et al. (2006), a T-statistic is considered acceptable when it exceeds the following thresholds: 1.96 for a 95% confidence interval, 1.65 for a 90% confidence interval, 2.57 for a 99% confidence interval, and 3.29 for a 99.9% confidence interval. These criteria help determine the robustness of the relationships between the variables in the model.

Table 6. Hypothesis Testing

Hyp	**Relations**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Level of sign.**	**Decison**
H1	EP -> TA	0.136	2.018	0.044	***	Accepted
H2	EE -> TA	0.1	2.81	0.005	***	Accepted
H3	SI -> TA	0.152	1.429	0.153	n.s	Rejected
H4	FC -> TA	0.085	9.471	0.000	***	Accepted
H5a	GENDER x EP -> TA	0.152	0.712	0.476	n.s	Rejected
H5b	GENDER x EE -> TA	0.099	1.816	0.069	n.s	Rejected
H5c	GENDER x SI -> TA	0.175	1.028	0.304	n.s	Rejected
H6a	GRADE x SI -> TA	0.103	0.922	0.357	n.s	Rejected
H6b	GRADE x EE -> TA	0.098	1.107	0.269	n.s	Rejected
H6c	GRADE x FC -> TA	0.115	1.334	0.182	n.s	Rejected

H7a	EXPERIENCEATTHEGRADE x EE -> TA	0.12	1.858	0.063	n.s	Rejected
H7b	EXPERIENCEATTHEGRADE x SI -> TA	0.102	1.035	0.301	n.s	Rejected
H7c	EXPERIENCEATTHEGRADE x FC -> TA	0.123	1.772	0.076	n.s	Rejected
H8	TA -> PP	0.05	14.35	0.000	***	Accepted
H9	TA -> IP	0.067	7.445	0.000	***	Accepted

Source: Authors based on Smart PLS 4.

**** = P values < 0.001 and n.s. = not significant.

TA = Technology Adoption, FC = Facilitating Conditions, EE = Expected Effort, SI = Social Influence, EP = Expected Performance, IP= Innovative Performance, PP = Professional Performance.

According to the bootstrap T-statistics rules, hypotheses are accepted when the T-statistic exceeds 1.65. Thus, relationships such as: PA -> ATN with T-statistic = 2.018 > 1.65 and p-value = 0.044 < 0.1; EA -> ATN with T-statistic = 2.81 > 1.65 and p-value = 0.005 < 0.1; CF -> ATN with T-statistic = 9.471 > 1.65 and p-value = 0.000 < 0.1; ATN -> PP with T-statistic = 14.35 > 1.65 and p-value = 0.000 < 0.1; and ATN -> PI with T-statistic = 7.445 > 1.65 and p-value = 0.000 < 0.1 are all accepted. However, relationships such as IS -> ATN with T-statistic = 1.429 < 1.65 and p-value = 0.153 > 0.1, as well as relationships involving the moderating variables, are all rejected.

5. Discussion and Implications of the Results

Before engaging in a detailed discussion and exploring the implications of the results, a summary table of the main interpretations from the analysis is first presented to structure and contextualize the model's observations.

5.1 Discussion of the Significance of the Main Results in Relation to the Hypotheses and Existing Literature

In the context of external auditing within the OHADA region, this study found that Expected Performance (PA) plays a significant role in the adoption of digital technologies by auditors. This aligns with the findings of Venkatesh & Davis (2000), who noted that employees are more likely to adopt systems that they expect will improve their performance. Similarly, Brown, Dennis, & Venkatesh (2010) and Bader & Mohammad (2019) confirmed that Expected Performance influences technology adoption. Auditors adopt digital technologies primarily because they enhance productivity, performance, and work quality.

Regarding Expected Effort (EA), which reflects the ease of using technology (Brown, Dennis, & Venkatesh, 2010), the results align with Zhou, Lu, and Wang (2010), who found that ease of use encourages technology adoption. This is also consistent with Matabishi (2019) and Bader & Mohammad (2019), who concluded that the less effort required, the more likely technology will be adopted.

For Facilitating Conditions (CF), the results support Venkatesh (2003), Brown, Dennis, & Venkatesh (2010), and Zhou, Lu, and Wang (2010), who found that available resources positively influence technology adoption. Bader & Mohammad (2019) also highlighted the importance of facilitating conditions in adoption. This suggests that resources that support technology use influence auditors' adoption (Allbabidi, 2021).

However, Social Influence (IS) did not impact auditors' adoption of digital technologies, which contrasts with the findings of Venkatesh (2003), Ling et al. (2012), and Brown, Dennis, & Venkatesh (2010). This could be due to the hierarchical positions of the target population (senior, manager, and senior manager), which require the use of technology regardless of social influence.

Finally, the adoption of digital technologies positively impacts auditors' performance, consistent with Allbabidi (2021), who found that technology enhances operational efficiency and provides auditors with new skills. This is further supported by Al-Ansi (2015), who emphasized that technology helps auditors improve both professionally and innovatively, as noted by Duan, Deng, & Wibowo (2024), who distinguished between Professional and Innovative Performance.

5.2 Implications

The implications of this study are threefold. First, from a theoretical perspective, this study is one of the first in the auditing context to apply the UTAUT theory to understand technology adoption and link it to the TACT theory, assessing how technology adoption enhances auditors' performance. It contributes to the literature on audit and digitalization by proposing a model to measure these concepts, which are often assessed through TOE (Technology-Organization-Environment), TAM (Technology Acceptance Model), or TCP (Theory of Planned Behavior) due to respondent scarcity. The UTAUT theory, which requires a large number of respondents, faces limitations when applied to strategically positioned auditors who are not supported, posing a challenge for researchers using this framework.

Second, from a practical perspective, the study suggests that auditors' performance is tied to their use of digital technologies. Auditors who view technology use as an advantage are positively evaluated, helping them advance in a profession increasingly shaped by digital tools. Additionally, the study serves as a caution to students considering a career in audit firms, emphasizing that their performance will be assessed not only on core knowledge like accounting and auditing but also on their proficiency with digital technologies.

6. Conclusion

The future profile of auditors will require not only in-depth industry knowledge but also advanced technological skills. Performance evaluations, based on assignments and annual reviews, will determine auditors' progression in a "promotion to partner process," aiming to retain those who meet the required standards. This study aimed to understand the use of digital technologies by auditors in the OHADA region using the UTAUT and TACT theories. The results showed that Expected Performance, Expected Effort, and Facilitating Conditions influence the use of digital technologies by auditors and enhance their performance. These findings were compared with previous research to assess their relevance.

However, the study has limitations. The lack of a comprehensive survey base of audit firms using digital technologies prevented full representation, and although the OHADA region includes 17 member countries, only 12 were included due to practical and logistical constraints.

The study's implications lead to several recommendations: First, researchers should enhance quantitative studies in auditing to better understand issues like digital technologies, auditor performance, audit quality, and independence, supported by audit firms or strategically positioned auditors for a larger sample. Second, audit firms yet to integrate technologies are encouraged to adopt them to improve service quality and align with the digital age's business model, which will help improve performance. Third, business schools and universities, as the source of auditors, should update training programs to integrate technology, providing practical learning to better prepare students for success in audit firms, ultimately leveraging their performance.

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Authors' contributions

Patient Cirimwami Matabishi developed the theoretical framework and research model, collected the data and carried out the statistical analyses. Ivan Djossa Tchokoté constructed the research design, selected the methodological tools and analysed the research results. Both authors participated in the handwriting of the article.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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References

Abreu, P. W., Aparicio, M., & Costa, C. J. (2018). Blockchain technology in the auditing environment. *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*. https://doi.org/10.23919/CISTI.2018.8399460

Aissaoui, A., & Abdelghaffar, S. M. (2021). Points de démarrage pour l'analyse PLS-SEM: spécificités et optimisation de l'usage et de l'interprétation avec la méthode. *Centre International d'Innovation et de Développement*, 18.

Al-Ansi, A. (2015). *IT fit on auditors' performance in Yemen*. Universiti Utara Malaysian Electronic Theses and Dissertation.

Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). *Corporate Governance and Organizational Behavior Review*, *6*(1), 64-78. https://doi.org/10.22495/cgobrv6i1p5

Al-Sayyed, S., Al-Aroud, S., & Zayed, L. (2021). The effect of artificial intelligence technologies on audit evidence. *Accounting*, *7*(2), 281-288. https://doi.org/10.5267/j.ac.2020.12.003

Albawwat, I., & Frijat, Y. (2021). An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality. *Accounting*, *7*(4), 755-762. https://doi.org/10.5267/j.ac.2021.2.009

Allbabidi, M. (2021). Hype or Hope: Digital Technologies in Auditing Process. *Asian Journal of Business and Accounting*, *14*. https://doi.org/10.22452/ajba.vol14no1.3

Allouli, N., & Boumeska, M. (2023). L'Impact de la transformation digitale sur l'audit externe: Nouvelles perspectives et pratiques émergentes: Revue systématique de littérature. *Alternatives Managériales Economiques*, *5*(4), 135-153.

Atik Yildirim, A. (2021). Blockchain Technology and Its Potential Effects on Accounting: A Systematic Literature Review. *Istanbul Business Research (IBR)*, *50*(2), 495-515.

Bader, A. A., & Mohammad, A. Y. Y. (2019). The impact of task technology fit on employee job performance. *Marketing and Management of Innovations*, *4*, 140-159. https://doi.org/10.21272/mmi.2019.4-12

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, *27*(2), 9-54. https://doi.org/10.2753/MIS0742-1222270201

Chu, M. K., & Yong, K. O. (2021). Big data analytics for business intelligence in accounting and audit. *Open Journal of Social Sciences*, *9*(9), 42-52. https://doi.org/10.4236/jss.2021.99004

Chung, S., Lee, K. Y., & Kim, K. (2014). Job performance through mobile enterprise systems: The role of organizational agility, location independence, and task characteristics. *Information & management*, *51*(6), 605-617. https://doi.org/10.1016/j.im.2014.05.007

Cockcroft, S., & Russell, M. (2018). Big data opportunities for accounting and finance practice and research. *Australian Accounting Review*, *28*(3), 323-333. https://doi.org/10.1111/auar.12218

Cristea, L. M. (2021). Romanian auditors' perception concerning the IT impact in the big data era. *Public Finance Quarterly= Pénzügyi Szemle, 66*(S1), 68-82. https://doi.org/10.35551/PFQ_2021_s_1_4

Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, *205*, 219.

Davis, W. J. (1984). Motivation and learning: Neurophysiological mechanisms in a "model" system. *Learning and Motivation*, *15*(4), 377-393. https://doi.org/10.1016/0023-9690(84)90004-3

Deloitte, L. (2017). *Delivering smarter audits.* Insights through innovation. In.

Duan, S. X., Deng, H., & Wibowo, S. (2024). Technology affordances for enhancing job performance in digital work. *Journal of Computer Information Systems*, *64*(2), 232-244. https://doi.org/10.1080/08874417.2023.2188497

Evrard, Y., Pras, B., & Roux, E. (2003). Market: études et recherches en marketing: fondements, méthodes. *Dunod*, (3ème ed.), Paris.

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process?. *Review of Accounting Studies*, *27*(3), 938-985. https://doi.org/10.1007/s11142-022-09697-x

Goff, I. B.-L. (2019). Sébastien Stenger, Au cœur des cabinets d'audit et de conseil. De la distinction à la soumission. *Sociologie du travail [En ligne]*, *61*(4), 286. https://doi.org/10.4000/sdt.28444

Hair, J., *et al.*. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, *46*(1-2), 1-12. https://doi.org/10.1016/j.lrp.2013.01.001

Hair, J., *et al.*. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* Thousand Oaks CA: Sage.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). In: Pearson Prentice Hall. New Jersey.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook.* Springer Nature. https://doi.org/10.1007/978-3-030-80519-7

Hasan, A. R. (2021). Artificial Intelligence (AI) in accounting & auditing: A Literature review. *Open Journal of Business and Management*, *10*(1), 440-465. https://doi.org/10.4236/ojbm.2022.101026

Henry, H., & Rafique, M. (2021). Impact of Artificial Intelligence (AI) on Auditors: A Thematic Analysis. *IOSR Journal of Business and Management*, *23*(9).

Jensen, M. C., & Meckling, W. H. (2019). Theory of the firm: Managerial behavior, agency costs and ownership structure. In *Corporate governance* (pp. 77-132). Gower.

Laitinen, E. K., & Laitinen, T. (2015). A probability tree model of audit quality. *European Journal of Operational Research*, *243*(2), 665-677. https://doi.org/10.1016/j.ejor.2014.12.021

Ling, K. M., Ramayah, T., Kurnia, S., & May Chiun, L. (2012). Explaining intention to use an enterprise resource planning (ERP) system: an extension of the UTAUT model. *Business Strategy Series*, *13*(4), 173-180. https://doi.org/10.1108/17515631211246249

Louwers, T. J., Blay, A. D., & Sinason, D. H. (2018). *Auditing & assurance services*. McGraw-Hill.

Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). The digital transformation of external audit and its impact on corporate governance. *Technological Forecasting and Social Change*, *150*, 119751. https://doi.org/10.1016/j.techfore.2019.119751

Matabishi. (2019). *Adoption de la banque monbile par les étudiants de la ville de Bukavu en R.D Congo*.

Mighiss, S., & Kabbaj, S. (2021). L'audit à l'ère de la transformation digitale. *Revue du contrôle, de la comptabilité* *et de l'audit*, *5*(3).

Mione, M., Barucci, E., Marazzina, D., Rana, V., Bruschi, F., & Gianturco, P. (2020). *Deloitte Blockchain galaxy*. https://doi.org/10.13140/RG.2.2.10284.49288

Mohd Noor, N. F., Mohd Sanusi, Z., Johari, R. J., Saad Al-Dhubaibi, A. A., Hudayati, A., & Abdul Razak, N. (2022). An examination of the utilization of audit technology in influencing audit job performance. *Asian-Pacific Management Accounting Journal*, *17*(1), 283-309. https://doi.org/10.24191/APMAJ.V17i1-11

Montes, G. A., & Goertzel, B. (2019). Distributed, decentralized, and democratized artificial intelligence. *Technological Forecasting and Social Change*, *141*, 354-358. https://doi.org/10.1016/j.techfore.2018.11.010

Pugna, I. B., & Duţescu, A. (2020). Blockchain–the accounting perspective. *Proceedings of the International Conference on Business Excellence*. https://doi.org/10.2478/picbe-2020-0020

Rogers, E. M. (1995). Diffusion of Innovations: modifications of a model for telecommunications. *Die diffusion von innovationen in der telekommunikation*, 25-38. https://doi.org/10.1007/978-3-642-79868-9_2

Schmitz, J., & Leoni, G. (2019). Accounting and auditing at the time of blockchain technology: a research agenda. *Australian Accounting Review*, *29*(2), 331-342. https://doi.org/10.1111/auar.12286

Schuberth, F., Henseler, J., & Dijkstra, T. K. (2018). Partial least squares path modeling using ordinal categorical indicators. *Quality & Quantity*, *52*, 9-35. https://doi.org/10.1007/s11135-016-0401-7

Silva, R., Inácio, H., & Marques, R. P. (2022). Blockchain implications for auditing: a systematic literature review and bibliometric analysis. *International Journal of Digital Accounting Research*, *22*. https://doi.org/10.4192/1577-8517-v22_6

Taşar, S., & ErkuŞ, H. (2022). The adaptation of independent audit profession to the digital era. *İnönü University International Journal of Social Sciences (INIJOSS)*. https://doi.org/10.54282/inijoss.1116491

Tiberius, V., & Hirth, S. (2019). Impacts of digitization on auditing: A Delphi study for Germany. *Journal of International Accounting, Auditing and Taxation*, *37*, 100288. https://doi.org/10.1016/j.intaccaudtax.2019.100288

Üçoğlu, D. (2020). Current machine learning applications in accounting and auditing. *Pressacademia*, *12*, 1-7. https://doi.org/10.17261/Pressacademia.2020.1337

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. https://doi.org/10.2307/30036540

Wilson, A. B., McNellis, C., & Latham, C. K. (2018). Audit firm tenure, auditor familiarity, and trust: Effect on auditee whistleblowing reporting intentions. *International Journal of Auditing*, *22*(2), 113-130. https://doi.org/10.1111/ijau.12108

Zemánková, A. (2019). Artificial intelligence and blockchain in audit and accounting: Literature review. *Wseas Transactions on Business and Economics*, *16*(1), 568-581.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, *26*(4), 760-767. https://doi.org/10.1016/j.chb.2010.01.013