JOBED | JOURNAL OF BUSINESS AND ENTERPRISE DEVELOPMENT

Volume 13 Issue 1

ISSN NO: ISSN-L (online): 2026-500X **Journal Homepage:** https://journal.ucc.edu.gh/index.php/jobed

Determinants of Audit automation adoption among audit firms in Ghana

Cornelius Adorm-Takyi (PhD)[a*] George Tackie (PhD)[a] Anthony Adu-Asare Idun (PhD)[b]

[a] Department of Accounting, School of Business, University of Cape Coast, Ghana

[b]Department of Finance, School of Business, University of Cape Coast, Ghana

DOI: https://doi.org/10.47963/jobed.v13i.1731

*Corresponding Author: ctakyi@ucc.edu.gh

To cite this Paper: Adorm-Takyi, C., Tackie , G. ., & Idun , A. A.-A. Determinants of audit automation adoption among audit firms in Ghana . *Journal of Business and Enterprise Development (JOBED),* 13(1). https://doi.org/10.47963/jobed.v13i.1731

Article Information

Keywords:
Audit automation adoption
UTAUT
Audit firms
Ghana
PLS-SEM
IPMA

Received: 15th March 2025
Revised: 20th April 2025
Accepted: 27th April 2025

Editor: Anthony Adu-Asare Idun

Abstract

Automation is widely recognised to be revolutionising the auditing profession. Despite the known benefits, it is reported that auditors are not fully leveraging the potential value of certain automated tools and techniques. To understand why, this study aims to draw on the unified theory of acceptance and use of technology (UTAUT) to empirically examine the determinants of audit automation adoption by audit firms in Ghana. The study conforms to the positivist paradigm which agrees with the quantitative approach and an explanatory research design; structured questionnaires were administered to 190 respondents from various audit firms in good standing with the Institute of Chartered Accountants Ghana (ICAG) using Google Forms. Partial least squares structural equation modelling (PLS-SEM) via Smart PLS was used for the analysis and testing of the hypotheses. Importance performance map analysis (IPMA) was conducted to enhance a deeper understanding of the findings. Performance expectancy and effort expectancy have a positive and significant influence on audit automation adoption by audit firms in Ghana. This implies that auditors will be willing to use audit automation when they perceive that it will enhance their performance and that the use of audit automation will mean less effort will be required from the auditors. The study contributes to the literature by advancing the understanding of the importance of performance expectancy and effort expectancy as determinants of audit automation adoption. This extends the theoretical understanding of the UTAUT model.

Introduction

In recent years, audit automation has emerged as a transformative trend within the auditing profession, driven by the need for enhanced efficiency, accuracy, and consistency in audit practices (Dasinapa & Ermawati, 2024; Appelbaum *et al.*, 2020). Audit automation technologies streamline traditionally manual processes, enabling auditors to analyse vast amounts of data, monitor compliance in real time, and detect anomalies or fraud with greater precision (Ganapathy, 2023; Islam & Stafford, 2022; Awuah *et al.*, 2022; Elommal & Manita, 2022). It also minimises workload and routine processes, increases efficiency, lowers audit costs, provides a thorough audit trail, improves data analytics, enhances risk assessment, and ensures efficient sampling (Handoko et al., 2020; Cohen & Rozario, 2019). For audit firms in Ghana, the adoption of audit automation holds significant potential for improving the quality of audit engagements and staying competitive in a rapidly evolving global business landscape.

Audit automation is described as the use of computers in the management, planning, performance and completion of audits to eliminate or reduce time spent on computational or clerical tasks, to improve the quality of audit judgements, and to ensure consistent audit quality (Fotoh and Lorentzon, 2023; Zhang *et al.,* 2022; Siew, Rosli, & Yeow, 2020; Institute of Chartered Accountants England and Wales [ICAEW], 2018; Manson *et al.,* 1998). This study examines the adoption of specific automation tools—Generalized Audit Software (GAS), Electronic Audit Working Papers Software, Embedded Audit Modules, Database SQL Search and Retrieve, Parallel Simulation Software, and Test Data—as proxies for understanding the adoption landscape in Ghanaian audit firms (Serpeninova, Makarenko & Litvinova, 2020). These tools collectively cover essential aspects of audit automation—data extraction, continuous monitoring, digital documentation, real-time validation, and advanced control testing. Together, they embody the comprehensive skill set and technology stack required for effective audit automation. Tracking their adoption provides insight into the level of technological advancement and the strategic priorities of audit firms in implementing automated solutions. By focusing on these proxies, auditors can assess both the technological readiness of audit firms and the factors influencing their approach to adopting audit automation.

The use of electronic data via Computer Assisted Audit Techniques (CAATs) is recognised by the International Standard on Auditing (ISA) 330 as a feasible option for acquiring audit evidence. This may be employed either as a substitute or as a complementary method alongside current control mechanisms. Auditors may use automated tools and techniques (ATT) to facilitate the gathering of information about an entity's business and organisational structure, as well as to enhance their understanding of transaction flows and processing in alignment with ISA 315 (updated 2019), particularly paragraph A57. According to the International Standard on Auditing (ISA) 500, the use of audit automation may augment the auditor's capacity to detect any occurrences of misrepresentation or fraudulent conduct inside the financial statement.

The current study modelled a theoretical framework for successful audit automation adoption through the lens of the unified theory of acceptance and use of technology (UTAUT) and suggested that the factors influencing the auditors' use of CAATT are performance expectancy, effort expectancy, social influence, and facilitating conditions (Owino and Musuva, 2021; Pedrosa *et al.,* 2020; Mahzan and Lymer, 2014; Venkatesh *et al.,* 2003).

Despite the tremendous advantage of using automation in all audit engagements (Fotoh and Lorentzon, 2023; Doğanay, 2019; Bierstaker *et al.,* 2014), numerous recent studies suggest that the use of automation by auditors remains unsatisfactory (Zhang *et al.,* 2022; Kend & Nguyen, 2020; Moffitt *et al.,* 2018; Curtis & Payne, 2014). According to Byrnes *et al.* (2018) and Moffitt *et al.* (2018), audit firms continue to execute their audit operations using traditional audit procedures that are primarily manual. Appelbaum *et al.* (2018) conducted preliminary research that demonstrated external auditors have not used numerous functions and facilities of computer-assisted auditing tools and techniques (CAATTs). Instead, auditors primarily use fundamental functions such as analytical procedures. The outcome is an imbalance between automated transaction processing on the side of the firms and manual audit procedures on the side of the auditors, which results in a higher cost of the audit and a lower quality of the audit (Emett *et al.,* 2021; Kang & Piercey, 2020).

In addition, extraordinarily little consideration has been given to the factors that influence the adoption of audit automation by external auditing firms. Studies conducted in this field concentrated their attention on the application of technology in the setting of an internal audit (Awuah *et al.,* 2022; Li *et al.,* 2018; Mahzan & Lymer, 2014). Furthermore, previous research with mixed results indicates that performance expectancy, effort expectancy, facilitating conditions and social influence as explained by the unified theory of acceptance and use of technology (UTAUT) as determinants of audit automation adoption (Owino & Musuva, 2021; Pedrosa *et al.,* 2020; Mahzan & Lymer, 2014; Venkatesh, et al., 2003).

Even though there has been a substantial amount of discussion both within and outside of academic circles regarding how automation affects the auditing process, the existing body of literature on the subject appears to be heavily shaped by the experiences of industrialized countries. Moreover, no prior research had been undertaken applying the UTAUT model to audit automation adoption in the case of Ghana leaving a contextual study gap in under-developed counties, especially those in Africa such as Ghana. Because of this, it has become necessary to conduct research in the context of a developing country such as Ghana to supplement the growing body of knowledge and to contribute to the discussion regarding the determinants of audit automation adoption in the auditing process.

This research aims to address the critical question: how do performance expectancy, effort expectancy, facilitating conditions, and social influence collectively shape the decision-making process and adoption of audit automation within professional auditing firms? The lack of a comprehensive understanding of these factors hinders the development of targeted strategies for successful adoption, potentially impeding the realization of the full potential of audit automation in enhancing audit processes. This underscores the need for a deeper exploration into the intricate interplay of these variables to inform practitioners, policymakers, and scholars on effective approaches to navigate and accelerate the adoption of audit automation in the contemporary audit environment.

The rest of this paper is organised as follows: Section two focuses on the theoretical review, while Section three examines the empirical review and hypotheses development. Section four concentrates on the research methodology. Section five concentrates on the empirical results and provides a detailed discussion of the empirical results. Finally, Section 6 focuses on the conclusions and direction for further research.

Literature Review

Unified theory of acceptance and usage of technology (UTAUT)

The study employed the unified theory of acceptance and usage of technology (UTAUT) model to explain the determinants of audit automation adoption. This theory was developed by Venkatesh *et al.* (2003) to provide a comprehensive framework for understanding the factors that influence an individual's adoption of information technology (IT). The components of the UTAUT model consist of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) (Venkatesh *et al.*, 2003). The theory was developed through a comprehensive assessment, comparison, and trial of eight competing ideas within the field of research.

The effectiveness of the UTAUT has been proven to be a valid theory for technology adoption behaviour. Hence, the model has garnered much acclaim in comparison to other models, mostly due to its simplicity, cost-effectiveness, and robustness. Moreover, the empirical data has provided evidence to support the superiority of this model when compared to other previously prevalent models in the area (Venkatesh *et al.*, 2003; Zhang *et al.*, 2022).

Despite the extensive replication, utilisation, and integration of the UTAUT model, several scholars contend that there is still a need for a systematic investigation and conceptualisation of the key factors related to the adoption of technology in particular contexts (Venkatesh *et al.*, 2003). Furthermore, it is important to acknowledge that the UTAUT model, has not been extensively evaluated in the specific setting of a developing nation like Ghana when it comes to being used to explain the determinants of audit automation adoption by audit firms (Owino and Musuva, 2021).

Performance expectancy and audit automation adoption

Performance expectancy highlights the degree to which a person holds the opinion that the implementation of a certain system will contribute to enhancing their performance (Venkatesh *et al.*, 2003). Based on established auditing rules and guidelines, the incorporation of audit automation can enhance the efficiency and efficacy of external audits (International Standard on Auditing [ISA] 315, 200, 500). Moreover, prior studies on automation have shown that the utilisation of automation aids auditors in improving their understanding of their client's information technology controls, simplifying risk assessment during the planning stage, and enhancing the efficiency of audit testing. Hence, there is a prevalent belief that the use of audit automation can augment the efficacy of external auditors. Existing literature has consistently shown a significant influence of performance expectancy on the adoption of computer-assisted audit tools and techniques (CAATT) (Pedrosa *et al.*, 2020; Ramen *et al.*, 2015; Rosli *et al.*, 2012; Janvrin *et al.*, 2008; Curtis and Payne, 2008; Venkatesh *et al.*, 2003). The study, therefore, examines the effect of performance expectancy on audit automation and proposes that:

H1: Performance expectancy has a significant influence on audit automation adoption.

Effort expectancy and audit automation adoption

Effort expectancy refers to the degree of user happiness and usability that the adopter associates with the technology being evaluated (Venkatesh *et al.*, 2003). This construct specifically relates to people's perceptions of the ease of using technology. The UTAUT model suggests that, in similar conditions, the likelihood of external auditors adopting automation is higher when the technology is designed to be user-friendly. This eliminates the requirement for a difficult learning process to effectively use automation.

Existing research indicates that the proficiency of auditors in the field of information technology/information systems (IT/IS) has a significant influence on the extent to which audit automation is embraced. Multiple studies (Pedrosa *et al.*, 2020; Ramen *et al.*, 2015; Gonzalez *et al.*, 2012; Rosli *et al.*, 2012; Janvrin *et al.*, 2008; Curtis and Payne, 2008; Venkatesh *et al.*, 2003) have provided evidence indicating that auditors with a significant level of IT/IS competency tend to exhibit a reduced perception of effort expectancy when it comes to embracing audit automation. The study, therefore, examines the effect of effort expectancy on audit automation and proposes that:

H2: Effort expectancy has a significant influence on audit automation adoption.

Social influence and audit automation adoption

Social influence refers to the degree to which a person perceives that others value the importance of adopting new technologies (Venkatesh *et al.*, 2003). The decision regarding the adoption of automation within an organisation can be impacted by a range of factors, such as the viewpoints and outlooks of the audit partner, colleagues within the auditing firm, and other professional connections (Pedrosa *et al.*, 2020; Ramen *et al.*, 2015; Rosli *et al.*, 2012; Janvrin *et al.*, 2008; Curtis and Payne, 2008; Venkatesh *et al.*, 2003). Ferri *et al.* (2021) and Gonzalez *et al.* (2012) concluded that social influence affects auditors' acceptance of continuous auditing and blockchain technology, respectively. Curtis and Payne (2014) proved that social influence positively affects auditors' intentions to use CAAT. The study, therefore, examines the effect of social influence on audit automation and proposes that:

H3: Social influence has a significant influence on audit automation adoption.

Facilitating conditions and audit automation adoption

Venkatesh *et al.* (2003) define the concept of facilitating conditions as an individual's subjective assessment of the degree to which the organisational and technical infrastructure is accessible and capable of facilitating the adoption of a certain technology. The factors that can influence external auditors' adoption of automation include the availability of sufficient information about the capabilities of automation, support from vendors or software providers, and endorsement from top-level management in their organisations. Previous scholarly research examining the association between facilitating conditions and the adoption of technology adoption has consistently revealed a positive influence on the acceptance of technology (Pedrosa *et al.*, 2020; Ramen *et al.*, 2015; Rosli *et al.*, 2012; Janvrin *et al.*, 2008; Curtis and Payne, 2008; Venkatesh *et al.*, 2003). Pedrosa *et al.* (2020) and Bierstaker *et al.* (2014) found that the adoption and use of CAAT were triggered by supporting conditions that facilitated it. The study, therefore, examines the effect of facilitating conditions on audit automation and proposes that:

H4: Facilitating conditions have a significant influence on audit automation adoption.

Research Methods

Research design

The study is grounded on the philosophical framework of positivism. The use of the positivist paradigm for this research is justified since it assumes of rational human acts and beliefs and facilitates the comprehension of behaviour via the process of hypothesis testing (Blumberg *et al.*, 2014). The application of the quantitative research approach and the explanatory research design is in accord with the positivist paradigm (Creswell and Creswell, 2017).

The study's population consisted of all audit companies in Ghana that maintained a favourable status with the Institute of Chartered Accountants, Ghana (ICAG) as of 2022. According to the ICAG, there were a total of 329 audit firms that had valid licenses as of the end of the year 2022 (ICAG, 2022). The study employed a simple random sampling technique in which random numbers were generated with computer applications and those numbers that correspond with the codes for the elements in the sampling frame were contacted through the use of Google Forms which were sent to emails of the respondents (Kneusel, 2018; Creswell and Creswell, 2017; Cohen *et al.*, 2017; Blumberg *et al.*, 2014). According to Al-Hiyari *et al.* (2019), the use of Google Forms has shown its effectiveness and suitability in expeditiously acquiring data from external auditors. The process of data gathering spanned two months, commencing on July 1st, 2022 and concluding on August 31st, 2022. The study had 190 respondents.

Data collection instrument and measurement

The data-gathering process included the use of a questionnaire. The use of a questionnaire in this research is justified due to its capacity to elicit answers that are both accurate and trustworthy, hence enabling the generalization of findings to the broader study population (Zikmund *et al.*, 2013). Additionally, this method affords participants the chance to allocate sufficient time for thoughtful responses and allows for the inclusion of large samples, hence facilitating the acquisition of trustworthy and valid outcomes (Zikmund *et al.*, 2013). Key ethical issues such as privacy, confidentiality, non-manipulation of data and results, informed consent and formal permission were keenly observed to preserve the sanctity of the study.

To mitigate the occurrence of non-return or non-response rate and response bias, the questionnaire was constructed following established criteria for questionnaire design. The design of the questions employed in this study used straightforward, non-debatable, and clear language. Furthermore, the questions were arranged in a manner consistent with the funnel technique, which involves starting with general inquiries before progressing to more specific ones (Creswell and Creswell, 2017; Cohen *et al.*, 2017; Blumberg *et al.*, 2014). To ensure the validity of the questionnaire, it underwent a rigorous evaluation and pre-test process including two audit practitioners and three academics that specialize in the relevant research area. Following this evaluation, a pilot test of the instrument was conducted with 30 respondents to identify problematic items and further improve the survey.

The questionnaire was divided into three sections. Section A collected demographic data on the respondents which included gender, age, highest educational qualification, and professional qualifications. Section B collected data on the independent variables (performance expectancy, effort expectancy, facilitating conditions and social influence). Table 1 indicates the operationalisation of the independent variables. Participants were instructed to use a five-point Likert scale, where 1 represented "Strongly disagree" and 5 denoted "Strongly agree." They were then asked to indicate their degree of agreement or disagreement by marking the relevant box with a checkmark (√) (Awuah *et al.*, 2022; Siew *et al.*, 2020; Pedrosa *et al.*, 2020; Pallant, 2020; Hair *et al.*, 2019; Pimentel, 2019).

Section C gathered data about the dependent variable (audit automation adoption). Table 2 indicates the operational measurement of the dependent variable. The respondents were instructed to use a five-point Likert scale where, 0% (never use) and 100% (extensively used) to indicate the percentage of audit tasks conducted through these audit automation tools by ticking [√] the appropriate box (Siew *et al.*, 2020; Braun and Davis, 2003). The audit automation adoption was measured with six indicators which included the following audit tools: generalized audit software, electronic audit working papers software, embedded audit modules, parallel simulation software, and test data (Siew *et al.*, 2020).

Table 1: Operational measurement of the independent variables

Indicators	Items	Operational definition	Source
Performance Expectancy (PE)	4	Corresponds to individual performance and perceived utility because of adopting audit automation	Venkatesh *et al.* (2003) Venkatesh *et al.* (2012)
Effort Expectancy (EE)	4	The degree of ease that auditors perceive when they adopt audit automation in their auditing tasks	Venkatesh *et al.* (2003) Janvrin *et al.* (2008) Curtis and Payne (2014)
Social Influence (SI)	4	The degree to which an individual perceives that other people are important to them and believes they should adopt audit automation	Venkatesh *et al*. (2003) Janvrin *et al.* (2008) Curtis and Payne (2014)
Facilitating Conditions (FC)	5	The degree to which an individual perceives that organisational and technical infrastructure exists to support the adoption of audit automation	Venkatesh *et al.* (2003) ; Janvrin *et al.* (2008); Mahzan and Lymer (2014); Curtis and Payne (2014)

Table 2: Operational measurement of dependent variables

Variables	Indicators	Operational definition	Source
Audit automation adoption	Generalized audit software	Audit software helps the auditor access the client's system database, extract relevant data, and perform an analysis of the audit function.	Janvrin *et al.* (2008) Mahzan and Lymer (2014) Mahzan and Lymer (2014); Bierstaker *et al.* (2014); Siew *et al.* (2020)
	Electronic audit working papers software	Software that produces a trial balance and other schedules useful to record evidence in an audit or assurance engagement	Braun and Davis (2003) Siew *et al.* (2020)
	Embedded audit modules	Programmed audit module incorporated into client's application programme to identify transactions that meet auditor's measures. The identified transaction is reviewed in real time or in batches.	Braun and Davis (2003) Siew *et al.* (2020)
	Database SQL search and retrieve	Software that uses relational structures between data files and query language that facilitates data retrieval and use.	Braun and Davis (2003) Siew *et al.* (2020)
	Parallel simulation software	Abstraction of the client's application system that is developed to imitate the results produced by the client's application. The auditor may use a model to compare the results and evaluate the reliability of information generated by the client's system.	Braun and Davis (2003) Siew *et al.* (2020)
	Test data	A set of transaction input data prepared by an auditor to test the application program or procedural operations.	Braun and Davis (2003) Siew *et al.* (2020)

Data processing and analysis

The data were analysed using IBM Statistical Product and Service Solutions (SPSS) Version 22 and Smart PLS-SEM Version 4. The SPSS was used to analyse the demographic statistics of the respondents, the descriptive statistics of the constructs and the assessing common method bias. The categorical data was analysed by generating frequencies, while numerical data was analysed by computing measures of central tendency such as the mean and standard deviation.

Partial least square structural equation modelling (PLS-SEM) was used to assess the measurement model, and the structural model (Hair et al., 2019). PLS-SEM is a nonparametric method and, unlike covariance-based structural equation modelling, makes no distributional assumptions and readily incorporates both reflective and formative measures (Hair *et al.*, 2019).

The standard PLS-SEM estimations were then complemented with an importance-performance map analysis (IPMA). IPMA has been recently applied in the context of PLS-SEM to enable researchers to gain richer and more precise insights from their findings because it simultaneously considers both the path coefficient estimates and the average values of the latent variable scores (Ringle and Sarstedt, 2016).

Results

Summary of respondents' demographics

The demographic characteristics used for the study included gender, age, educational qualification, and professional qualification (Table 3). The results of the demographic analysis indicated that most participants were males (84.7%). The modal age group was 20-30 (40.7%). Concerning educational qualification, 49.5% had master's degrees and 72.6% were chartered accountants.

Table 3: Summary of respondents' demographics

Variables	Options	Frequencies (N=190)	Percentages (%)
Gender	Male	161	84.7
	Female	29	15.3
Age	20-30	77	40.5
	31-40	66	34.7
	41-50	31	16.3
	51-60	12	6.3
	61 and above	4	2.2
Educational Qualification	Diploma certificate	3	1.6
	Bachelor's degree	87	45.8
	Master's degree	94	49.5
	Doctorate	6	3.1
Professional Qualification	Chartered accountant	138	72.6
	Other professional qualification	4	2.1
	No professional qualification	48	25.3

Descriptive statistics of constructs

Table 4 provides the descriptive statistics of the various constructs used in the study. It indicates the mean scores as measures of central tendency and standard deviation as measures of dispersion. In general, the mean values of the items and constructs exceeded 2.5. When using a five-point Likert scale to assess variables, with higher values indicating more positive, a score of 2.5 would be regarded as the mean or average. The lowest mean score was recorded by item SI4 (M=2.890, SD=1.197) and the highest was recorded by item AAA3 (M=3.440, SD=1.100). Effort expectancy had the highest mean score (M=3.373, SD=1.190) while social influence had the lowest mean score (M=2.933, SD=1.165).

Table 4: Descriptive Statistics of the Constructs

Constructs	Items	Mean (M)	Std. Deviation (SD)
Performance expectancy	PE1	3.330	1.222
	PE2	3.260	1.253
	PE3	3.260	1.091
	PE4	3.190	1.190
		3.260	**1.189**
Effort expectancy	EE1	3.370	1.235
	EE2	3.350	1.184
	EE3	3.340	1.169
	EE4	3.430	1.170
		3.373	**1.190**
Social influence	SI1	2.930	1.187
	SI2	2.930	1.118
	SI3	2.980	1.159
	SI4	2.890	1.197
		2.933	**1.165**
Facilitating conditions	FC1	2.990	1.089
	FC2	2.960	1.172
	FC3	3.070	1.071
	FC4	3.050	1.140
	FC5	3.150	1.109
		3.044	**1.116**
Audit automation adoption	AAA1	3.110	1.112
	AAA2	3.140	1.290
	AAA3	3.440	1.100
	AAA4	3.440	1.249
	AAA5	3.330	1.155
	AAA6	3.350	1.259
		3.302	**1.194**

Measurement model assessment

A reflective measurement model best suited the study because causality is from the constructs to their measures/indicators. Hence, they were evaluated based on outer loadings, internal consistency reliability, convergent validity and discriminant validity (Hair *et al.*, 2019). The average variance extracted (AVE) was applied to assess convergent validity (Hair et al., 2019). The assessment of discriminant validity involves the consideration of three primary criteria, namely the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait (HTMT) ratio criterion (Henseler *et al.*, 2015). The results show that all the reflectively measured construct indicators are dependable and valid (Table 5).

The outer loadings exceeded 0.708 indicating that the constructs account for over 50% of the variation in the indicator (Hair *et al.*, 2019). Consequently, this level of loading ensures satisfactory item dependability. Two indicators for audit automation adoption (AAA1 and AAA2) were excluded from the analysis due to their reported loadings falling below the threshold of 0.708 (Table 5).

The assessment of reliability was conducted with Cronbach's alpha and composite reliability. The statistics for the constructs are above the required threshold of 0.70, (Table 5). This suggests that the dependability of the constructs is strong, hence, internal consistency reliability was met (Henseler *et al.*, 2015).

The convergent validity of the construct was deemed acceptable as shown by the fact that the average variance extracted (AVE) is above the minimum value of 0.50 (Hair *et al.*, 2019), as shown in Table 5.

To evaluate the discriminant validity of the constructs, the cross-loadings, Fornell-Larcker (1981) criterion, and the HTMT ratio were computed. The cross-loading findings indicate that the factor loadings of all the items exhibit greater strength on the underlying constructs to which they are associated, as opposed to the other constructs examined in the research (Hair *et al.*, 2019). The findings from Fornell-Larcker's (1981) criterion indicate that the square root of the average variance extracted (AVE) for the construct surpasses its correlation with all other constructs. Additionally, the heterotrait-monotrait ratio of correlations (HTMT) is below the threshold of 0.85 (Hair *et al.*, 2019). This indicates that discriminant validity has been achieved.

Table 5: Assessment of internal consistency reliability and convergent validity

Item	Indicator Loading	Cronbach's alpha	Composite reliability (rho_c)	AVE
Performance Expectancy (PE)				
PE1	0.854	0.883	0.919	0.739
PE2	0.848			
PE3	0.857			
PE4	0.880			
Effort Expectancy (EE)				
EE1	0.826	0.880	0.917	0.735
EE2	0.892			
EE3	0.849			
EE4	0.862			
Facilitaing Conditions (FC)				
FC1	0.731	0.880	0.905	0.657
FC2	0.745			
FC3	0.911			
FC4	0.787			
FC5	0.866			
Social Influence (SI)				
SI1	0.801	0.796	0.861	0.609
SI2	0.834			
SI3	0.755			
SI4	0.727			
Audit Automation Adoption (AAA)				
AAA3	0.861	0.878	0.916	0.732
AAA4	0.866			
AAA5	0.850			
AAA6	0.843			

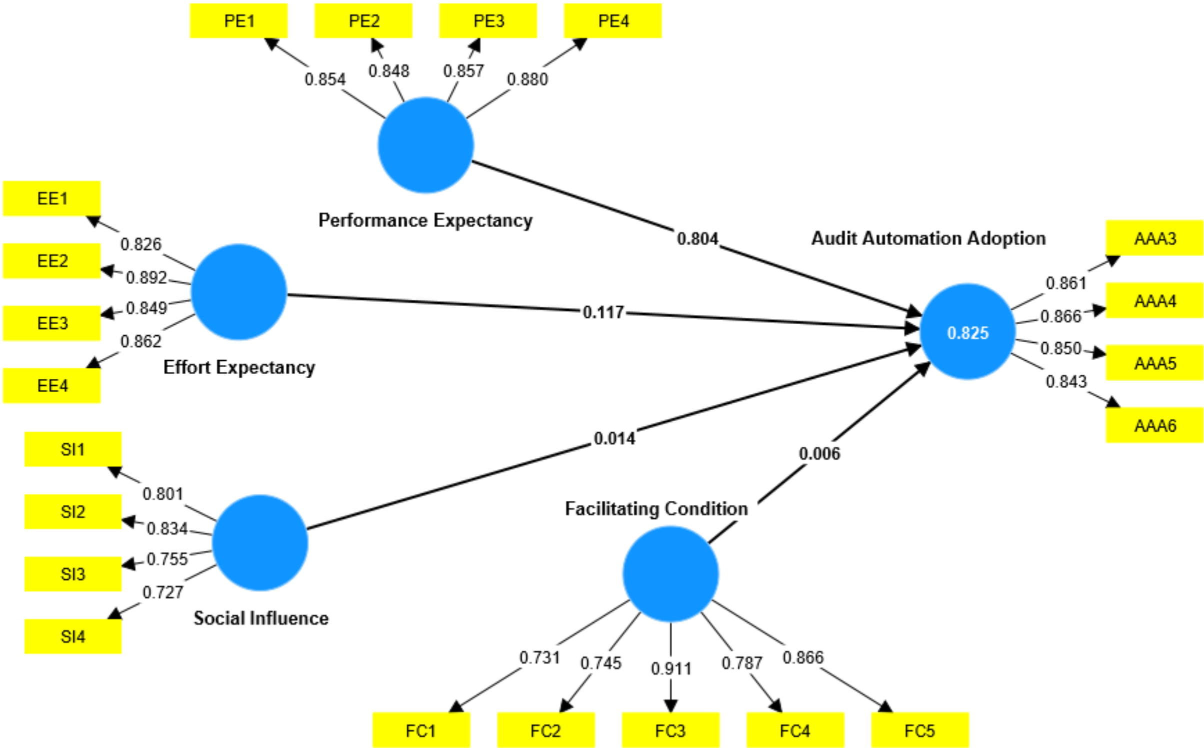

Figure 1: Measurement model

Structural model assessment

The evaluation of the structural model was conducted after the establishment of the measurement model. According to Hair *et al.* (2019), it is important to consider the standard assessment criteria when evaluating a structural model. These criteria include examining the presence of collinearity issues in the structural model, evaluating the significance and relevance of the relationships within the model, analysing the coefficient of determination (R^2), assessing the statistical significance and relevance of the path coefficients (f^2) and the predictive relevance (Q^2). Therefore, to ensure clarity and maintain consistency, the analysis of findings is structured following the aforementioned methodology.

The study checked the absence of collinearity issues by inspecting the values of the variance inflation factor (VIF). All VIF values were well below 5 (Hair *et al.*, 2019), highlighting that collinearity was not an issue (Table 6).

The results of the bootstrapping procedure with 5,000 samples revealed that two out of the four structural model relationships were significant (Table 6). This significance level was established at a t-statistic larger than or equal to 1.96 with corresponding p-values less than 5% (Greenland *et al.*, 2016).

Effort expectancy and performance expectancy have a positive and significant effect on audit automation adoption. Table 6 and Figure 2 provide the detailed results of the estimations.

Table 6: Significance testing results of the structural model path coefficients

Hypotheses	Relationship	Original sample	T statistics	P values	F^2	VIF
H1	PE -> AAA	0.804	15.283	0.000	1.050	3.509
H2	EE -> AAA	0.117	2.033	0.021	0.023	3.329
H3	SI -> AAA	0.014	0.326	0.372	0.001	2.116
H4	FC -> AAA	0.006	0.137	0.446	0.000	2.005

The analysis showed that effort expectancy ($B = 0.117$, $p < 0.05$) and performance expectancy ($B = 0.804$, $p < 0.001$) had positive and significant effects on audit automation adoption. Therefore, both H1 and H2 were supported. However, facilitating conditions and social influence did not have a significant effect on audit automation adoption and therefore not supported.

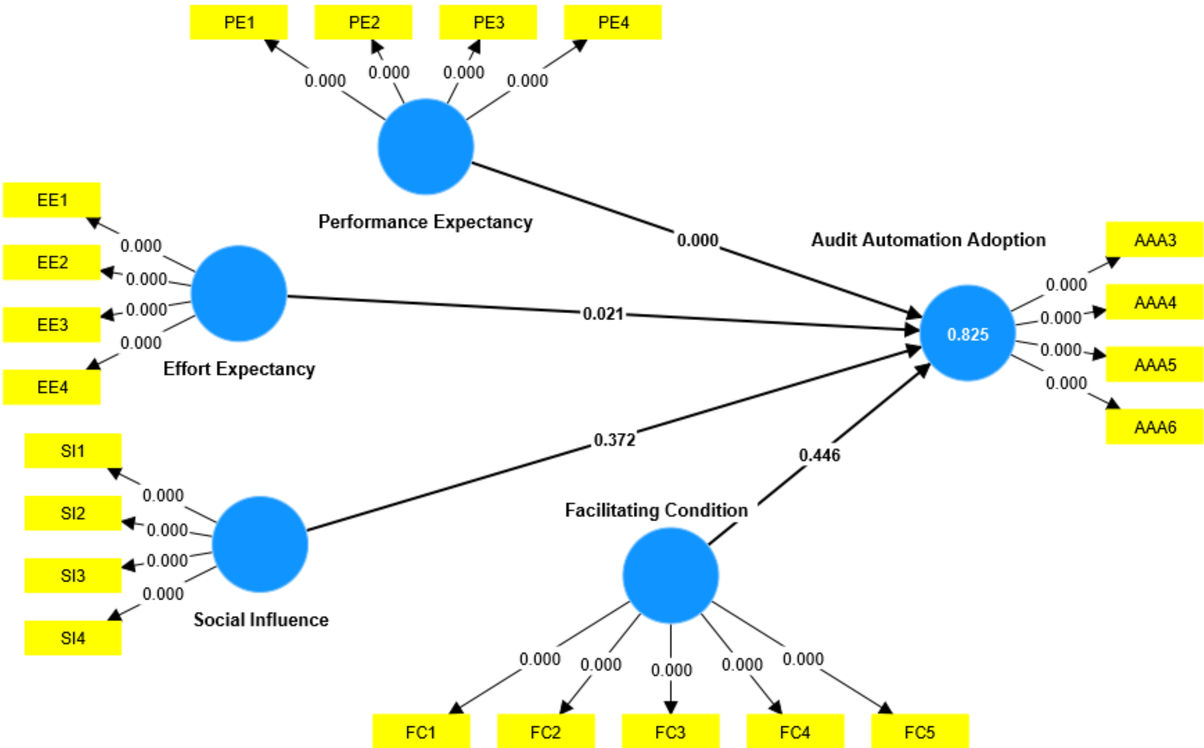

Figure 2: Structural model

Importance performance map analysis (IPMA)

The results of the importance-performance map analysis (IPMA) enriched the understanding and interpretation of the findings (which highlighted the importance of each construct) by also considering the performance of the constructs (Ringle and Sarstedt, 2016). The IPMA extends the reported PLS-SEM results of the path coefficient estimates using an analysis dimension that considers the average values of the latent variables' scores (Ringle and Sarstedt, 2016). As shown in Figure 3, performance expectancy and effort expectancy are the two constructs registering the highest importance and performance. This could explain their significant effect on audit automation adoption. On the other hand, social influence and facilitating conditions had the lowest importance and performance. This explains their insignificant effects on audit automation adoption.

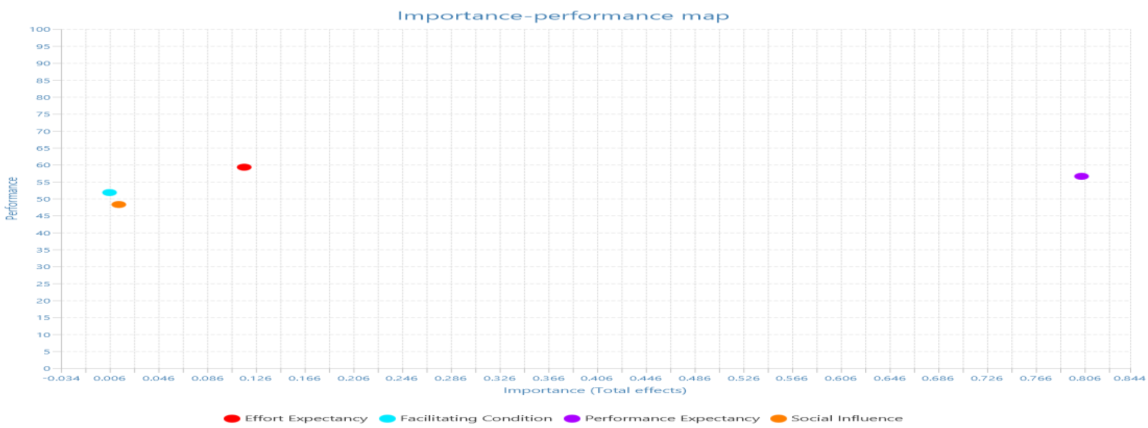

Figure 3: Variable IPMA

Figure 4 shows the results of the IPMA on the indicator level. These data highlight the specific aspects to improve. Among the items that measure performance expectancy, PE1 shows the highest level of importance and performance indicating that auditors use audit automation to obtain evidence on controls' efficacy. The Social influence indicators, specifically SI4 recorded the lowest level of importance and performance.

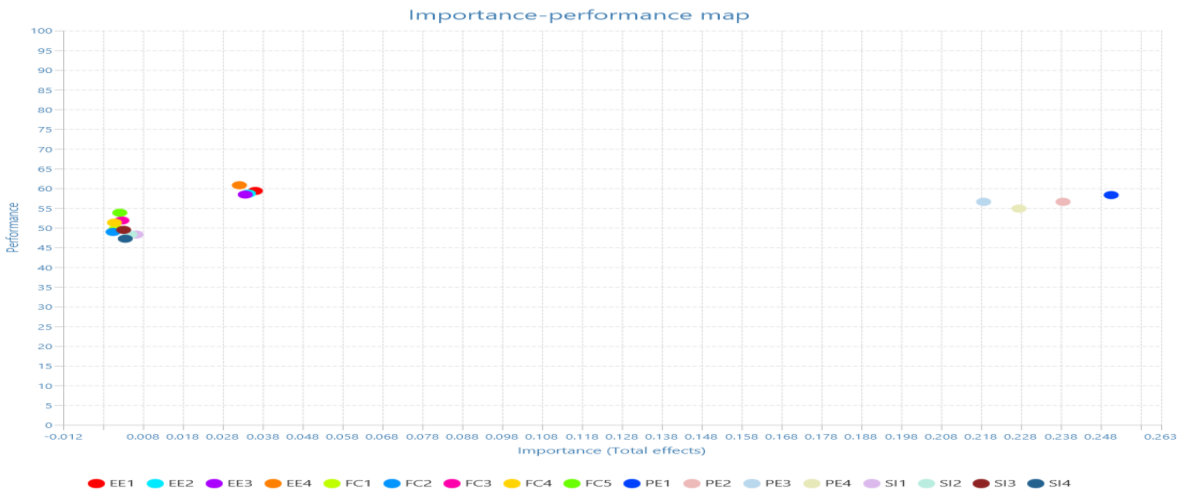

Figure 4: Indicator IPMA

In-sample model fit/ explanatory power (R^2)

To assess the model's in-sample fit, the study computed the R^2. The R^2 also known as the explanatory power, quantifies the proportion of variability in the response variable that can be explained by the predictor variables. This coefficient varies between 0 and 1. Higher values of R^2 indicate a stronger ability to explain the variability in the data. According to Henseler *et al.* (2015) and Hair *et al.* (2019), R^2 values of 0.75, 0.50, and 0.25 may be classified as substantial, moderate, and weak, respectively. Based on the findings of Hair *et al.* (2019) and Sarstedt et al. (2019), it has been established that a coefficient of determination value of at least 10% is deemed appropriate.

The findings presented in Table 7 demonstrate an R^2 coefficient of determination of 0.825. This suggests that 82.5% of the variability in audit automation adoption may be ascribed to performance expectancy, effort expectancy, social influence and facilitating conditions. The model's explanatory power can be characterized as substantial and therefore possessing predictive accuracy.

Table 7: Predictive accuracy (R^2 and R^2 adjusted) and Predictive relevance (Q^2)

	R-square	R-square adjusted	Q^2
Audit Automation Adoption	0.825	0.821	0.815

Effect size (f^2)

The effect size (f^2) is used to evaluate the contribution of each external construct to the R^2 value of the endogenous construct. According to Hair *et al.* (2019), this metric assesses the extent to which the removal of a certain variable has a significant impact on the dependent variable. Following the criteria of Benitez *et al.* (2020) for evaluating effect size (f^2: $0.02 \leq f^2 \leq 0.15$ (small effect size), $0.15 \leq f^2 \leq 0.35$ (moderate effect); $f^2 \geq 0.35$ (large effect size), performance expectancy had large effect size, effort expectancy had small effect size whiles facilitating

Predictive accuracy (Q^2)

Another means to assess the PLS path model's predictive accuracy is by calculating the Q^2 value (Hair *et. al.*, 2019). This metric is based on the blindfolding procedure that removes single points in the data matrix, imputes the removed points with the mean and estimates the model parameters (Sarstedt *et al.*, 2019). As such the Q^2 is not a measure of out-of-sample prediction but rather combines aspects of out-of-sample prediction and in-sample explanatory power (Sarstedt *et al.*, 2019).

As a guideline, Q^2 values are expected to be larger than zero (0) for a specific endogenous construct to indicate the predictive accuracy of the structural model for that construct (Hair *et al.*, 2019). The study established that the Q^2 is 0.815 (Table 7). The Q^2 value for the endogenous construct is, therefore, greater than zero, hence, predictive accuracy is established.

Out-of-sample predictive power

Finally, the model's out-of-sample predictive power was assessed using the PLSpredict routine which was computed by running it with 10 folds and 10 repetitions (Sarstedt *et al.*, 2022; Hair *et al.*, 2019). In the first step, all the indicators of audit automation adoption outperform the most naïve benchmark (i.e. the training sample's indicator means), as all the indicators yield $Q^2_{predict}$ values above 0 (Table 8). The study based its predictive power assessment on the RMSE because the visual inspection of the prediction errors suggests that the prediction is not highly non-symmetric. Comparing the RMSE values from the PLS-SEM analysis with the naïve LM benchmark (Table 8) reveals that the PLS-SEM analysis produced lower prediction errors for only AAA4. Thus, for the AAA3, AAA5, and AAA6, the RMSE values were greater than the LM values. This could be due to insufficient data.

Table 8: PLS predict

	Q^2predict	PLS-SEM_RMSE	LM_RMSE
AAA3	0.571	0.723	0.678
AAA4	0.549	0.843	0.861
AAA5	0.625	0.710	0.542
AAA6	0.628	0.769	0.537

The effect of performance expectancy on audit automation adoption

Hypothesis one which sought to examine the effect of performance expectancy on audit automation revealed that performance expectancy had a positive and significant effect on audit automation adoption (Table 6). This explains that when auditors feel the benefit of the use of audit automation is positive they will increasingly intend to use it in the audit process. Thus, audit automation will be more likely to be adopted if it is beneficial. This result is supported by prior literature (Pratama and Komariyah, 2023; Ferri *et al.*, 2021; Al-Hiyari *et al.*, 2019; Tansil *et al.*, 2019; Bierstaker *et al.*, 2014; Ahmi and Kent, 2013) but contrasting with the result by Gonzalez *et al.* (2012).

The effect of effort expectancy on audit automation adoption

Hypothesis two examined the effect of effort expectancy on audit automation adoption. The result of the PLS-SEM showed a positive and significant relationship between effort expectancy and audit automation adoption (Table 6). It can be interpreted that when an auditor perceives the ease of using audit automation, it will encourage the auditor to use the audit automation in the audit process. Thus, external auditors will prefer to use audit automation that has a basic feature with a low complexity. They assume that easy-to-use features are more accepted than features with high conceptual complexity this is because they will require less effort and time than traditional methods to complete the audit process. Therefore, audit firms can choose to use audit automation systems that have good user-friendly features, easy-to-understand instructions and clear instructions. The result of this study supports previous studies (Pratama and Komariyah, 2023; Tansil *et al.*, 2019; Gonzalez *et al.*, 2012). However, it contrasts with earlier studies (Ferri *et al.*, 2020; Pedrosa *et al.*, 2020; Al-Hiyari *et al.*, 2019; Mahazan and Lymer, 2014).

The effect of social influence on audit automation adoption

The result of hypothesis three was not significant, thus, social influence does not have any statistically significant effect on audit automation adoption (Table 6). This result could mean that auditors' usage of audit automation is not dependent on social influence. In this context, Venkatesh et al. (2003) found that social influence is an important factor in mandatory settings whereas in voluntary settings, it might not be significant. audit automation adoption may be early, as only a few auditors have attended the training and gained knowledge. In addition, auditors cannot easily find their close colleagues in their audit department as important people who can influence and teach them. This result supports previous studies (Pratama and Komariyah, 2023; Al-Hiyari *et al.*, 2019; Tansil *et al.*, 2019; Bierstaker *et al.*, 2014; Curtis and Payne, 2014). However, it differs from previous studies which argued that social influence has a significant effect on technology adoption in auditing (Ferri *et al.*, 2020; Gonzalez *et al.*, 2012; Venkatesh *et al.*, 2003).

The effect of facilitating conditions on audit automation adoption

The results further indicate that facilitating conditions do not have a statistically significant effect on audit automation adoption (Table 6). This indicates that auditors consider facilitating factors as unimportant when it comes to audit automation adoption. This result is confirmed by previous literature (Al-Hiyari *et al.*, 2019; Gonzalez *et al.*, 2012). This result differs from that of other studies (Pedrosa *et al.*, 2020; Tansil *et al.*, 2019; Bierstaker *et al.*, 2014).

Conclusions and Implications

This study aimed to prove empirically using UTAUT whether the independent variables (performance expectancy, effort expectancy, facilitating conditions and social influence) described influence the dependent variable (audit automation adoption). These independent variables are performance expectancy, effort expectancy, social influence, and facilitating condition. Based on the statistical result of Smart PLS 4 software, it is found that performance expectancy and effort expectancy had positive and significant effects on audit automation adoption. However, social influence and facilitating conditions did not have a statistically significant effect on audit automation adoption. The result is consistent with the UTAUT model and explains audit automation adoption by auditors.

The findings of this study have practical/managerial implications. First, management should develop easy-to-understand and easy-to-use technology for the auditor to become proficient with its use quickly. Second, since audit automation can aid in improving the quality of financial statements because they are effective techniques in detecting fraud and misappropriation management should disseminate the benefits offered by audit automation adoption to encourage its effective adoption and usage.

The study further contributes significantly to academia by providing empirical evidence on how performance expectancy, effort expectancy, social influence, and facilitating conditions shape the adoption of audit automation, addressing a gap in the literature often dominated by studies from developed economies. It also enriches the theoretical discourse on technology acceptance by applying UTAUT to the unique challenges and opportunities in Ghana's auditing sector. Additionally, it offers a localized perspective that can inform cross-cultural comparisons and adaptations of global theories.

Limitations and Suggestions for Further Research

The study sampled external auditors in Ghana, future research could extend the range of respondents by involving external auditors in other countries to see whether geographic location influences perceptions of auditor use of automation.

The study utilizes UTAUT to examine audit automation adoption. Specifically, the study focused on the effect of performance expectancy, effort expectancy, facilitating conditions and social influence on audit automation adoption. Future research could add some other variables and evaluate their moderating effects on these relationships. Nevertheless, this study provides valuable insights into how to increase audit automation adoption by external auditors in Ghana.

Informed consent

A survey statement was provided on the questionnaire to assure participants' confidentiality about their contributions towards this paper.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data Availability

Data available on request due to privacy/ ethical restrictions

References

Ahmi, A., & Kent, S. (2012). The utilisation of generalized audit software (GAS) by external auditors. *Managerial Auditing Journal*, Emerald Insight, 28(2), 88-113. https://doi.org/10.1108/02686901311284522

Al-Hiyari, A., Al Said, N.& Hattab, E. (2019). Factors that influence the use of computer-assisted audit techniques (CAATs) by internal auditors in Jordan. *Academy of Accounting and Financial Studies Journal*, 23(3) 1-15. https://doi.org/1528-2635-23-3-393

Appelbaum, D. A., Kogan, A., and Vasarhelyi, M. A. (2018). Analytical procedures in external auditing: A comprehensive literature survey and framework for external audit analytics. *Journal of Accounting Literature*, 40(1), 83-101. https://doi.org/10.1016/j.acclit.2018.01.001

Appelbaum, D., Budnik, S., & Vasarhelyi, M. (2020). Auditing and accounting during and after the COVID-19 crisis. *The CPA Journal*, 90(6), 14-19. Retrieved from https://www.proquest.com/scholarly-journals/auditing-accounting-during-after-covid-19-crisis/docview/2420174156/se-2

Awuah, B., Onumah, J. M., & Duho, K. C. T. (2022). Determinants of adoption of computer-assisted audit tools and techniques among internal audit units in Ghana. *The Electronic Journal of Information Systems in Developing Countries*, 88(2), https://doi.org/10.1002/isd2.12203

Benitez, J., Henseler, J., Castillo, A.,& Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information and Management*, 57(2). https://doi.org/10.1016/j.im.2019.05.003

Bierstaker, J., Janvrin, D., & Lowe, D. J. (2014), What factors influence auditors' use of computer-assisted audit techniques? *Advances in Accounting*, 30(1), 67-74. https://doi.org/10.1016/j.adiac.2013.12.005

Blumberg, B., Cooper, D., & Schindler, P. (2014), EBOOK*: Business research methods*, McGraw Hill.

Braun, R. L., & Davis, H. E. (2003). Computer-assisted audit tools and techniques: analysis and perspectives. *Managerial Auditing Journal*, 18(9), 725-731. https://doi.org/10.1108/02686900310500488

Byrnes, P. E., Al-Awadhi, A., Gullvist, B., Brown-Liburd, H., Teeter, R., Warren, J. D., & Vasarhelyi, M. (2018), Evolution of Auditing: From the Traditional Approach to the Future Audit, *In Continuous Auditing: Theory and Application*, Emerald Publishing 285-297. https://doi.org/10.1108/978-1-78743-413-420181014

Cohen, L., Manion, L., & Morrison, K. (2017), Action research, In *Research methods in education,* Routledge, 440-456. https://doi.org/10.4324/9781315456539

Cohen, M., & Rozario, A. (2019), Exploring the use of robotic process automation (RPA) in substantive audit procedures, *The CPA Journal* 89(7), 49-53.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Curtis, M. B., & Payne, E. A. (2014). Modelling voluntary CAAT utilization decisions in auditing. *Managerial Auditing Journal* 29(4) https://doi.org/10.1108/MAJ-07-2013-0903

Dasinapa, M. B., & Ermawati, Y. (2024). Insights into Emerging Trends Shaping the Future of Audit and Assurance. *Advances in Managerial Auditing Research*, *2*(2), 75-86.

Doğanay, D. (2019). *Identifying factors affecting auditors' adoption of computer-assisted audit tools and techniques (caatts): an empirical ınvestigation* (Master's thesis, Middle East Technical University).

Elommal, N., & Manita, R. (2022), How Blockchain Innovation could affect the Audit Profession: A Qualitative Study. *Journal of Innovation Economics Management*, 37(1), 37-63.

Emett, S. A., Kaplan, S. E., Mauldin, E., & Pickerd, J. S. (2021). Auditing with data and analytics: External reviewers' judgments of audit quality and effort. *Available at SSRN 3544973*. http://dx.doi.org/10.2139/ssrn.3544973

Ferri, L., Spanò, R., Ginesti, G., & Theodosopoulos, G. (2021). Ascertaining auditors' intentions to use blockchain technology: Evidence from the Big 4 accountancy firms in Italy", *Meditari Accountancy Research*, 29(5), 1063-1087. https://doi.org/10.1108/MEDAR-03-2020-0829

Fornell, C. & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error, *Journal of Marketing Research* 18(1), 39-50. https://doi.org/10.2307/3151312

Fotoh, L. E., & Lorentzon, J. I. (2023). Audit digitalization and its consequences on the audit expectation gap: A critical perspective", *Accounting Horizons*, 37(1), 43-69. https://doi.org/10.2308/HORIZONS-2021-027

Ganapathy, V. (2023). AI in auditing: A comprehensive review of applications, benefits and challenges. *Shodh Sari-An International Multidisciplinary Journal*, *2*(4), 328-343.

Gonzalez, G. C., Sharma, P. N., & Galletta, D. F. (2012). The antecedents of the use of continuous auditing in the internal auditing context. *International Journal of Accounting Information Systems*, 13(3), 248-262. https://doi.org/10.1016/j.accinf.2012.06.009

Greenland, S., Senn, S. J., Rothman, K. J., Carlin, J. B., Poole, C., Goodman, S. N., & Altman, D. G. (2016). Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. *European Journal of Epidemiology*, 31, 337-350. https://doi.org/10.1007/s10654-016-0149-3

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

Handoko, B. L., Lindawati, A. S. L., & Mustapha, M. (2020). Application of computer-assisted audit techniques in a public accounting firm", *International Journal of Management*, 11(5), 222-229. https://doi.org/10.34218/IJM.11.5.2020.022

Harman, H. H., & Harman, H. H. (1976), *Modern factor analysis*. University of Chicago Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*. 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Institute of Chartered Accountants England and Wales. (2018), "Artificial Intelligence and the Future of Accountancy, Available via: https://www.icaew.com/media/corporate/files/technical/informationtechnology/technology/artificial-intelligence-report.ashx?la=en.

Institute of Chartered Accountants, Ghana [ICAG] (2022). https://icagh.org/ list-of-licensed-firms/

Islam, S., & Stafford, T. (2022). Factors associated with the adoption of data analytics by internal audit function. *Managerial Auditing Journal*, 37(2), 193-223. https://doi.org/ 10.1108/MAJ-04-2021-3090

Janvrin, D., Bierstaker, J., & Lowe, D. J. (2008). An examination of audit information technology use and perceived importance, *Accounting Horizons*, 22(1), 1-21. https://doi.org/10.2308/acch.2008.22.1.1

Kang, Y. J., & Piercey, M. D. (2020). Would an Audit Judgment Rule Improve Audit Committee Oversight and Audit Quality? *Current Issues in Auditing*, 14(1), 16-25. https://doi.org/10.2308/ciia-52644

Kend, M., & Nguyen, L. A. (2020). Big data analytics and other emerging technologies: the impact on the Australian audit and assurance profession, *Australian Accounting Review*, 30(4), 269-282. https://doi.org/10.1111/auar.12305

Kneusel, R. T. (2018). *Random numbers and computers*, Cham (CH): Springer, 239. https://doi.org/10.1007/978-3-319-77697-2

Li, H., Dai, J., Gershberg, T., & Vasarhelyi, M. A. (2018). Understanding usage and value of audit analytics for internal auditors: An organizational approach, *International Journal of Accounting Information Systems*, 28, 59-76. https://doi.org/10.1016/j.accinf.2017.12.005

Mahzan, N., & 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*, 29(4). https://doi.org/10.1108/MAJ-05-2013-0877

Manson, S., McCartney, S., Sherer, M., & Wallace, W. A. (1998). Audit automation in the UK and the US: A comparative study", *International Journal of Auditing*, Vol. 2, No. 3, pp. 233-246. https://doi.org/10.1111/1099-1123.00042

Moffitt, K. C., Rozario, A. M., and Vasarhelyi, M. A. (2018), Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting*, 15(1), 1-10. https://doi.org/10.2308/jeta-10589

Owino, B., and Musuva, P. (2021). Empirical Assessment of Improved Audit Quality Factors Using Computer-Assisted Audit Tools and Techniques (Caatts). *Journal of Language, Technology and Entrepreneurship in Africa*, 12(2), 147-171.

Pallant, J. (2020). *SPSS survival manual: A step-by-step guide to data analysis using IBM SPSS*. McGraw-Hill Education (UK). https://doi.org/10.4324/9781003117452

Pedrosa, I., Costa, C. J., & Aparicio, M. (2020). Determinants adoption of computer-assisted auditing tools (CAATs). *Cognition, Technology and Work* 22(3), 565-583. https://doi.org/10.1007/s10111-019-00581-4

Pimentel, J. L. (2019). Some biases in Likert scaling usage and its correction. *International Journal of Science: Basic and Applied Research (IJSBAR)*, 45(1), 183-191. Retrieved from https://www.gssrr.org/index.php/JournalOfBasicAndApplied/article/view/9874

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879. https://doi.org/10.1037/0021-9010.88.5.879

Pratama, F. W., & Komariyah, E. F. (2023). Examining the Auditors' Acceptance of Big Data Analytics Technology Platform: Evidence from Government Auditors in Indonesia", *The Indonesian Journal of Accounting Research*, 26(2), 273-302.

Ramen, M., Jugurnath, B., & Ramhit, P. (2015). UTR-CTOE: a new paradigm explaining CAAT adoption, *Journal of Modern Accounting and Auditing*, 11(12), 615-631. https://doi.org/10.17265/1548-6583/2015.12.001

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial management and data systems*, 116(9), 1865-1886. https://doi.org/10.1108/IMDS-10-2015-0449

Rosli, K., Yeow, P. H., & Siew, E. G. (2012). Factors influencing audit technology acceptance by audit firms: A new I-TOE adoption framework. *Journal of Accounting and Auditing*, 1-11. https://doi.org/10.5171/2012.876814

Sarstedt, M., Hair Jr, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ)*, 27(3), 197-211. https://doi.org/10.1016/j.ausmj.2019.05.003

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., and Ringle, C. M. (2022), "Progress in partial least squares structural equation modelling use in marketing research in the last decade", *Psychology and Marketing*, 39(5), 1035-1064. https://doi.org/10.1002/mar.21640

Serpeninova, Y., Makarenko, S., & Litvinova, M. (2020). Computer-assisted audit techniques: Classification and implementation by auditor. *Public Policy and Accounting*, *1* (1), 44-49.

Siew, E. G., Rosli, K., & Yeow, P. H. (2020). Organizational and environmental influences in the adoption of computer-assisted audit tools and techniques (CAATTs) by audit firms in Malaysia. *International Journal of Accounting Information Systems*, 36, https://doi.org/10.1016/j.accinf.2019.100445

Tansil, A. Y. M., Widuri, R., Gui, A., & Ali, M. M. (2019). Generalised Audit Software use by external auditor: An empirical examination from UTAUT. *International Journal of Innovation, Creativity and Change*, 5(2), 887-908.

Venkatesh, V., & Bala, H. (2012). Adoption and impacts of inter-organizational business process standards: Role of partnering synergy. *Information Systems Research*, 23(4), 1131-1157. https://doi.org/10.1287/isre.1110.0404

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

Zhang, C. A., Thomas, C., & Vasarhelyi, M. A. (2022). Attended Process Automation in Audit: A Framework and A Demonstration. *Journal of Information Systems*, 36(2), 101-124. https://doi.org/10.2308/ISYS-2020-073

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business research methods*. Cengage Learning.