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The role of artificial intelligence in achieving auditing quality for small and medium enterprises in the Kingdom of Saudi Arabia

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A B S T R A C T

This study seeks to investigate the variables that affect small and medium enterprises (SMEs) adoption of the usage of artificial intelligence (AI) and audit quality analysis from the perspectives of external auditors and accountants in the Kingdom of Saudi Arabia (KSA). Additionally, it seeks to determine whether external auditors and accountants in Saudi SMEs have different perspectives on AI adoption and how it affects audit quality. Data were gathered via an internet questionnaire from eighty accountants and forty audit companies in Saudi SMEs to accomplish these research goals. The study's findings indicate that accountants and external auditors in the KSA believe that utilizing AI improves the quality of audits. Also, it was discovered that there is no statistically significant difference in how accountants and auditors evaluate 'AI's contribution to audit quality.

1. Introduction

Every kind of organization functions in a changing environment and requires ongoing adaptation. Higher management must therefore make essential decisions leading to prompt and effective activities promoting conformance to new environments. Incorporating artificial intelligence (AI) methods in such decision-making is a crucial step in obtaining the highest level of efficacy. AI is significantly changing how firms approach problem-solving in decision-making. Following the fundamental changes brought about by Industry 4.0, AI and humans now work together to develop solutions to the challenging problems of our day and improve our ability to make better decisions and educate oneself (Psarras et al., 2022). Auditing aims to assess a company's financial and non-financial information and put the systems and processes in place to record and compile it for accuracy and credibility. This includes performing numerous audits of the firm's financial operations and procedures, speaking with management, gathering proof to support claims and account statuses, and physically verifying asset valuations. An auditor is a person or corporation a company hires to conduct such an audit. The objective is to form an opinion regarding the absence of significant misstatements resulting from fraud or errors in the company's financial statements. An auditor statement in the company's annual report states this conclusion (Ajao et al., 2016). To increase the effectiveness and efficiency of the audit process, audit firms are investing some money in innovative technological advancements. According to experts, the "Big 4" companies invest $250 million annually in artificial intelligence (AI). Using AI is defined as creating computer systems with improved decision-making abilities, the capacity for perceiving their environment and responding in a way that reduces the chance of failing to achieve a goal. Additionally, AI systems may develop behavioral norms and predictive models from massive data, making it possible to consume, manage, and run analyses on data. Auditors can quickly obtain insights from data from numerous sources when obtaining audit evidence. By actively connecting with both internal and external parties, the auditor can better understand the audit process's many steps (Albawwat & Frijat, 2021).

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The application of AI technology helps to increase the auditing process' accuracy and effectiveness. It is helpful in spotting potential problems in accounting procedures. It also helps spot potential problems with financial statements and books for firms. AI implementation helps further to increase the precision of a firm's accounting methods. In addition to that, technology has improved the caliber of audits. The application of AI has made it possible to conduct audits quickly, accurately, and completely. It has additionally been an effective technique for lowering the possibility of human errors (Kaplan & Haenlein, 2019). Small and midsize businesses (SMEs) are the backbone of any nation, generating income and jobs and assisting in the expansion and diversification of the economy. In emerging nations, formal SMEs account for up to 60% of all employment and up to 40% of GDP, according to the World Bank. If the informal sector is considered, these percentages will rise even further. In addition, the World Bank predicts that 600 million workers will be needed in the next 15 years, particularly in Asia and Sub-Saharan Africa. In many nations worldwide, SMEs account for a sizable portion of current employees and future growth opportunities. SMEs in Saudi Arabia contribute roughly 22% of the GDP, compared to 70% in certain other economies, according to the Ministry of Labor and Social Development. In Saudi Arabia, SMEs barely contribute 5% to exports. Small and medium-sized businesses (SMEs) employ about 34% of Saudi workers. Nearly 85% of these SMEs are single proprietor enterprises (Tripathi, 2019). SMEs are essential for job creation and economic growth. Their customer portfolios comprise a sizable component of auditing firms' clientele in several economies (Boukedjane, 2022).

Auditor specifications for quality assurance, adherence to new guidelines, and thorough management of auditors' work with SMEs have recently increased. SME auditing has become more time-consuming, expensive, and risky because of the auditing profession's evolution. Coordination, uniformity, and automation may be a remedy for optimizing the auditors' jobs and saving expenses in SME auditing (Ha & Nguyen, 2020). One area of focus for auditors while auditing SMEs is fraud detection, which is based on data and information that is readily available. Invoices, contracts, meeting minutes, bank transaction records, annual reports of organizations, and other readily available documentation of organizational activities are among the data available for such work. Most items are accessible digitally; however, many SMEs still only use printed materials. Significant blunders and gross carelessness are the primary operations that could possibly be automated. Comparing invoice statements with annual reports, discovering abnormalities, and spotting fraud are some of the most resource-intensive tasks performed by auditors, in addition to acquiring and collecting relevant data (Rikhardsson et al., 2022).

This study varies from previous research in the following areas. The primary purpose of this research is to investigate how external auditors and accountants in Saudi SMEs perceive AI's contribution to audit quality. In contrast, most research focus on AI in large companies and massive data and audit processes. Additionally, it frequently restricts itself to techniques based on neural networks and machine learning (Alles et al., 2020; Cooper et al., 2018; Kokina & Davenport, 2017). In comparison, Rikhardsson et al. (2022) investigated the AI applications that auditors could anticipate finding most useful when auditing SMEs. Noordin and Hussainey (2022) investigated the perception of the use of (AI) in the United Arab Emirates according to national and international external auditors. As a result, the current paper aims to add the following to the body of knowledge. We begin by adding to the literature by emphasizing the role of AI in auditing quality. However, in the current auditing literature, the external auditors and accountant SMEs' perceptions of AI on audit quality have not been examined in the Kingdom of Saudi Arabian. Second, there are limited studies on AI and SME auditing worldwide, including in the Kingdom of Saudi Arabia, and the quality of the research in this field is still lacking. Our article thus closes this research gap.

2. Literature Review and Hypotheses Development

2.1. Theoretical Framework

Artificial Intelligence is defined as the art and science of creating machines that behave in ways and act autonomously. Human-designed systems respond to a complex goal by sensing their surroundings through data collection, interpreting the gathered structured or unstructured data, inferring conclusions based on the knowledge, or using the information deduced from data to make a choice. In recent years, AI's economic influence has significantly increased, and according to research, it will reach $15 billion by 2030 (Palomares et al., 2021). AI is a synthesis of software and hardware that functions similarly to the human brain and can make sophisticated judgments depending on the information at hand. AI-driven computer software solutions can enhance performance and simplify life for people by handling repetitive tasks (Yoon, 2020). AI is the capacity of robots to comprehend, think, and learn in a manner like that of humans. This suggests that it would be possible to imitate human intellect on machines (Lee & Tajudeen, 2020). Rikhardsson et al. (2022) stated that Applications and technological domains combined provide certain technologies, such as

- Inductive language programming: using formal logic and developing hypotheses based on those facts.
- Robotic process automation (RPA): this technique creates a list of guidelines and activities to carry out by observing how users interact with an application and conduct specific tasks to attain predetermined objectives.
- Expert systems: rely on coding rules to replicate human judgment and reasoning and address a particular class of issues.
- Decision networks are a collection of components and their probabilistic interactions that help solve issues and make better decisions by accounting for missing information.

-Artificial neural networks: able to learn to perform better without explicit guidance to enhance, goal-setting, and decision-making.

- Autonomous systems: comprise the nexus of robotics and AI are used, for instance, in manufacturing and self-driving cars.

2.2. Application of AI in Auditing

The Big 4 companies are outlining the advantages of AI for the auditing industry, including time savings, quicker data analysis, higher levels of accuracy, in-depth knowledge of business processes, and improved client service. (Munoko et al., 2020). Data mining, machine learning, speech and picture recognition, and semantic analysis are just a few of the related technologies that go under the umbrella term AI. Data mining combines statistics, machine learning and AI to find patterns in massive data sets. This is significant because 90% of all data is unstructured, and data volume constantly grows. Financial transactions are particularly relevant AI trends. Additionally, AI is utilized for auditing the user interface and any program documentation and logs (Gotthardt et al., 2020). Using AI techniques to overcome various audit and assurance task challenges. Analytical evaluation, analytical processes, materiality assessments, current concern determinations, as well as risk assessment are just a few of the intricate and crucial audit tasks. Deficient performance of these tasks has severe repercussions and leads to the failure of the audit mission. It is crucial to fully explore the potential for advancement by creating and deploying sophisticated AI applications (Baldwin et al., 2006). Robot Process Automation assists auditors in automating repetitive and manual rule-based duties. Emphasizing high-order thinking abilities and assisting the auditors in the audit execution and planning procedures may elevate the auditors' position and raise the auditing quality (Nonnenmacher et al., 2021).

Data processing, the auditing environment, the sources of evidence, and audit conclusions are all impacted by AI. Auditors must draw inferences, reach auditing conclusions, and form auditing opinions based on their knowledge, experience, and wisdom after acquiring and evaluating the evidence. AI comprehensive inference can potentially reduce the subjectivity of practitioners' judgment significantly. The presence of independent auditing judgment in the auditing process gets improved by AI (Gao & Han, 2021). Instead of merely testing a sample of the company's transactions, information technology enables an auditor to work with and analyze a vast amount of financial data or transactions. As a result, the advancement of contemporary technologies like AI and ML provides an auditor with a greater understanding of the company's operations, enabling them to recognize and evaluate the likelihood of risk in each audit area. To boost audit quality, the auditor must be conversant in and current with this new, innovative technology (Keskinen & Tarwireyi, 2019). Almost two-thirds of all revenue and jobs in Europe come from SMEs, which make up 99% of all enterprises (Omoteso, 2012). Enterprises of a certain size are required to be audited in nearly all European countries. This is one of the major elements influencing the creation of certain kinds of investigations in SMEs. Also, it can be challenging to find information about these kinds of businesses; their financial conditions are murky, it is possible that when there are going-concern issues, their income statistics will be changed, and it can be challenging to comprehend audit reports (Sánchez-Medina et al., 2019). Future applications of AI in the auditing industry should prioritize SMEs and the auditor's independence, among other things. Thus, auditing services can significantly improve the management of SMEs through improved financial condition credibility and increased control over records and systems. These services surely help to explain why so many businesses use external auditors, even if they are too small to be examined (Chung & Narasimhan, 2001). Additionally, audits offer several advantages to the business itself. For instance, an audit's findings can increase process effectiveness, lessen internal issues, and support regulatory compliance. Also, raise the caliber of financial reporting because it can lessen issues with knowledge asymmetry between a company and its financiers(Knechel et al., 2008).

2.2.2. Technology Acceptance Model

Venkatesh et al. (2003) revised eight famous technological theories, and they used information from four organizations collected over six months using three different measurement sites. They reached another measurement model that is called the Unified Theory of Acceptance and Use of Technology (UTAUT), which is a comprehensive paradigm (Chen & Zhou, 2016). Information systems researchers have focused much emphasis on technology acceptance. The models used in the IS literature can be used as a starting point for investigating the problem in accounting and auditing. Venkatesh et al. created and evaluated (UTAUT). The use of contemporary technology in an audit engagement has several risks and expenses, even while it may present prospects for improved efficiency and effectiveness. Implementing current technology carries additional risks, such as high expenditures brought on by challenges with implementation and training, a lack of technical support when required, and a failure to achieve expected efficiency and effectiveness improvements(Curtis & Payne, 2008). UTAUT can be distilled down to four key components (referred to as "constructs") that significantly and directly influence adoption intention and, consequently, actual usage in one or more of the distinct models:

- Performance expectancy: A person's confidence that employing the method they are considering adopting would enable them to improve their work performance.
- Effort expectancy describes the comfort adopters associate with using the system they are considering (Mahzan & Lymer, 2014).
- Social influence: The degree to which someone has faith that significant individuals believe they ought to utilize the new technology they are considering.

- Facilitating conditions: Characterized as the extent to which someone thinks that an institutional and there is a technology foundation in place to enable the use of the technology they are thinking about implementing(Dwivedi et al., 2019).

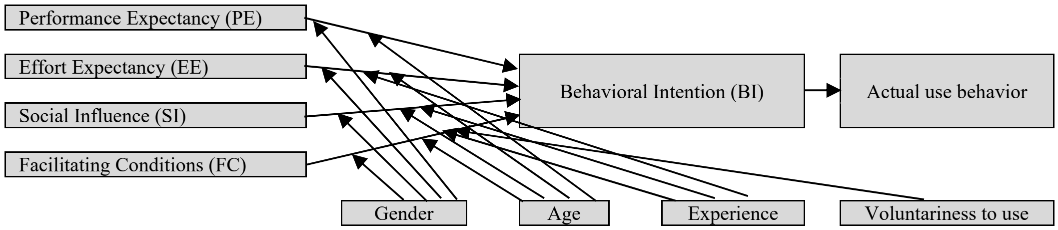

Fig. 1. Research framework adapted from the unified theory of acceptance and use of technology (UTAUT) model

2.3. Hypotheses Development

There has been further research on the interactions and adoption of AI technologies by auditors. (Hasan, 2022) stated that when presented with AI technology, humans accept it passively. Although people may not fully comprehend how it functions or what it is capable of, they embrace it as a part of their daily lives. Those who are inexperienced with AI technology or have unfavorable notions about it frequently accept it this way. When individuals use AI in a way that is advantageous to them or advances their objectives, this is referred to as active acceptance. They are aware of how it functions and can make use of it to enhance their lives. When someone accepts anything with skepticism, they do not think it is possible or do not believe in AI technology. They can be wary of its potential or believe that it will hurt them. Many studies dealt with using the model in the review, including (Gonzalez et al., 2012), which looks at the factors that led internal auditors to want to practice continuous auditing technology by using the UTAUT model. The study found that internal auditors' expectations regarding their level of responsibility and social impact are essential determinants. Also, the association between expected performance and social impact is strongly moderated by annual sales, firm volume, and voluntariness of use, respectively. Internal auditors in North America are more prone to adopt continuous auditing. On the other hand, if the higher authorities require the technology, Middle Eastern auditors are more inclined to use it. Dwivedi et al. (2019) conducted an initial attempt at applying UTAUT to IT adoption choices in the UK's internal audit sector in this study. To analyze the information from several interviews, the study found that two of the UTAUT constructs were found to be supported by the research (expectations for performance and facilitating conditions). Additionally, social impact and the other two UTAUT constructs, effort expectations, did not receive strong support. However, this study did not find the UTAUT components of social impact and effort expectancy as significant in this IT adoption. Abdolmohammadi (1991) explored audit responsibilities in AI through a list of tasks for audit partners and managers. The auditors were requested to identify the principal decision aid after receiving definitions and instructions relevant to each audit duty (to enhance strictly human processing). The findings show that the firm's structured, semi-structured, and unstructured audit methodology has a mixed impact on participants' decision-making. The complexity of the audit tasks and the participants' choice of auditor rank and specialist have a substantial impact.

Chung and Narasimhan (2001) polled small, limited companies and small audit firms to learn how they perceive the advantages of an audit, as these business types are most affected by the compulsory audit mandate. The results revealed that small audit firms that cater exclusively to Hong Kong's smaller enterprises now have more market opportunities thanks to the statutory audit obligation. The audit fee, on the other hand, puts small businesses in a difficult financial position because many of the users of their financial statements could not benefit financially from having them reviewed. Therefore, the required audit may seem like a waste of money for smaller businesses. The findings demonstrate that both groups of respondents find the small, limited company audit advantageous, especially considering its added benefits. Also, Huang et al. (2008) use the technology acceptance model (TAM) as the basic framework to analyze factors influencing the acceptability of computer-assisted audit techniques from the perspective of internal auditors. This study polls 117 internal auditors to test the model and then uses partial least squares in statistical analysis. The findings demonstrate that external variables (organizational support and system quality) have improved knowledge of the elements influencing perceived usefulness and usability. Another study (Knechel et al., 2008) explored the choices of auditors made by a sample of 2,333 small and mid-sized Finnish enterprises. All commercial enterprises in Finland must undergo a financial statement audit. However, the smallest companies are given the option of four auditing firms: international, national, second-tier local, and non-certified. The results showed that complexity initially drives the need for a higher-quality auditor among the smallest businesses. As the business grows, it is complemented by the need to raise equity and debt financing.

Aobdia (2019) investigated the degree of concordance between two audit process quality metrics obtained by internal audit firm inspections or inspections of specific engagements by the Public Company Accounting Oversight Board. The study found substantial correlations between both measures of audit procedure, such as audit fees, and three of the audit quality metrics used by academics. Seven academic proxies had insignificant relationships with practitioner assessments, and five had substantial associations with just one audit process quality indicator. A subsequent study (Sánchez-Medina et al., 2019) investigated the impact of a change in audit quality study elements in Spain in December 2010 regarding opinions changed for continued ambiguities. A total of 152 small and medium-sized businesses that had begun the bankruptcy process were examined, and they were analyzed by expert systems using classification trees built using boosting and bagging. Also, logistic regression served as a benchmark for comparing earlier techniques. The findings showed that auditors became more likely to disclose this circumstance, raising concerns about the audit's quality because of a shift in the norm that categorizes the going-concern issue as less significant. The main goal of the Puthukulam et al. (2021) study is to comprehend how auditors view the effects of internal auditors' opinions of how to increase audit efficiency. Several elements influencing their application and difficulties were considered to comprehend the influence of AI and ML. To collect data, a questionnaire was distributed to 189 people from several areas in Oman. According to the findings, professional skepticism and professional judgment have a substantial beneficial link with AI and ML-assisted auditing techniques. Additionally, it aids in the improvement of error and material misstatement detection. AI and ML must be used in conjunction with human interaction to increase auditing quality.

The study (Noordin & Hussainey, 2022) aimed to investigate how external auditors view the United Arab Emirates' usage of artificial intelligence (AI) (UAE). It investigates how external auditors see AI's role in improving the quality of audits. Additionally, it seeks to determine whether local and foreign external auditors have different perspectives on AI utilization and how it affects audit quality. Data from 66 audit firms were gathered via an online poll. The study found no statistically significant difference between local and multinational audit firms regarding how they evaluate AI's contributions to audit quality. All audit firms, whether domestic or foreign, are seen to contribute equally to audit quality. The study of (Fedyk et al., 2022) investigates the effects of artificial intelligence (AI) on audit effectiveness and quality. Moreover, it gives a preliminary impression of the AI workforce in the eight top US public accounting firms represented by 17 audit partners. The results indicated that most but not all AI employees are male, are relatively young, and have technical degrees. AI is a centralized function inside the company, with employees concentrated in a small number of teams and locations. Improved quality is the main objective of applying AI in audits, followed by increased efficiency. As a result, the following hypotheses are stated:

H_1: *There is a perception of external auditors and accountants in the Kingdom of Saudi Arabian that using AI contributes to audit quality.*
H_2: *The perceived contribution of AI usage to audit quality significantly differs between external auditors and accountants in SMEs in the Kingdom of Saudi Arabia.*

3. Research Design

3.1. Sample and Data

This study's population was made up of responses from external auditors and accountants at Saudi SMEs in the Emirate of Riyadh. The final sample consisted of 40 external auditors and 80 accountants from Saudi SMEs. A questionnaire survey gathered data for the current study. The study's purpose is described in the introduction paragraph, which also defines a few terminologies used in the questionnaire. In addition to the introduction, the questionnaire was divided into three parts: Questions about the experience, professional certifications, and educational credentials were asked in Section A .Section B measured independent variables based on the unified theory of acceptance and application of technology (UTAUT), which incorporates many technology acceptance models .Section C measures the dependent variable, "perceived contribution to audit quality".

3.2. Independent Variable and dependent Variable

The UTAUT is an integrated theory that defines how users adapt to, accept, and use technology. It combines many concepts of technology acceptance. Several broad implications about performance expectations, effort expectancy, social impact, and facilitating factors can be reached from various technological model studies. The concept contends that several factors affect users' choices regarding when and how to use contemporary technology for different objectives. The AI technology acceptance model pertains to how people interact with and accept AI's contribution to quality auditing. Dependent Variable according to Albawwat and Yaser (2021) and Noordin et al. (2022), who study on "The Use of Technology in the Audit of Financial Statements").

4. Data Analysis and Results

The data gathered for this research work were analyzed using Spss28 and Amos 26 statistical programs.

4.1. Exploratory Factor Analysis

Exploratory factor analysis (EFA) identifies Latent variables. Each latent variable is, then, loaded with a collection of survey questions. The researchers concluded that the phrases in the questionnaire loaded latent variables. Three phrases are loaded into the first latent variable, "Performance Expectancy," three phrases are loaded into the second latent variable, "Effort Expectancy," and two phrases are placed into the third latent variable, "Social Influence." The fourth latent variable (Facilitating

Circumstances) is loaded with three phrases. The fifth latent variable (Audit Quality), however, is loaded with nine phrases. According to Tables 1, 2, and 3, the KMO test result is 0.921. In case the KMO is greater than 0.60, the measure is appropriate. As a result, the sample size is appropriate for the research.

Table 1
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.921
Bartlett's Test of Sphericity	Approx. Chi-Square	246,169
	Df	158
	Sig.	.000

Table 2
Rotated Component Matrix

Phrases	Components of AI					
	Code	PE	EE	SI	FC	AQ
I can complete jobs more rapidly thanks to the system.	PE1	0.751				
My productivity increases when I use the system.	PE2	0.850				
My chances of receiving a raise will increase if I use the system.	PE3	0.524				
I could easily pick up the system's usage techniques.	EE1		0.609			
The system would be straightforward to use for me.	EE2		0.861			
I quickly learned how to operate the system.	EE3		0.777			
According to key persons, I should use the system.	SI1			0.586		
The senior management of company has been supportive of the system's implementation.	SI2			0.661		
I have everything I need to operate the system.	FC1				0.757	
I am familiar enough with the system to run it.	FC2				0.759	
There is a dedicated person on hand to help with any system issues.	FC3				0.686	
My professional skepticism will be aided by using AI systems and technologies in auditing.	AQ1					0.512
Automating basic audit processes and procedures with AI technologies and tools will free up more time to concentrate on areas that require substantial judgment.	AQ2					0.733
My comprehension of the entity and its operations will increase because of the use of AI systems and technologies in auditing.	AQ3					0.787
AI systems and auditing technology will permit thorough risk evaluation by evaluating large communities.	AQ4					0.757
A continuous risk assessment will be possible throughout the audit process thanks to the use of systems and technologies in auditing.	AQ5					0.773
Using AI tools and technology in auditing to stratify large populations will make it simpler to focus examinations on the regions with the greatest danger.	AQ6					0.653
The impartial replication of sophisticated computations and modeling will be made possible using AI techniques in auditing.	AQ7					0.763
Potential fraud will be found using AI techniques and systems in auditing.	AQ8					0.760
Unusual trends that might not be noticeable using more conventional audit procedures will be identified by applying AI systems and technologies in auditing.	AQ9					0.666

PE =Performance Expectancy, EE= Effort Expectancy SI= Social Influence
FC=Facilitating Conditions AI= Artificial Intelligence, AQ= Audit Quality

4.2. Confirmatory Factor Analysis

To make sure the factor structure derived from the EFA is plausible, confirmatory factor analysis (CFA) is performed. Following the testing, it was established that 20 indicators had been loaded with a coefficient of more than 0.50 on each of the five latent variables (PE, EE, SI, FC, and AQ); as shown in Fig. 2. This model took into consideration only the relationships between indicators and combination; assuming covariance between latent variables (Anderson & Gerbing, 1988). and table 3 shows model fit measures; extracted from the statistical analysis software AMOS 26.

Table 3
Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	246.169	--	--
DF	158	--	--
CMIN/DF	1.558	Between 1 and 3	Excellent
CFI	0.925	>0.90	Acceptable
RMSEA	0.068	0.05< RMSEA<0.08	Acceptable
LTI	0.91	>0.90	Acceptable
IFI	0.927	>0.90	Acceptable

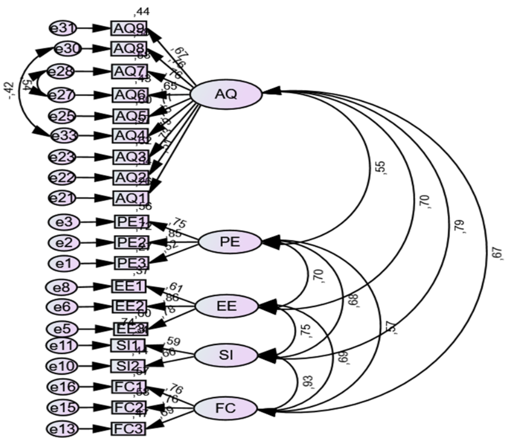

Fig. 2. Confirmatory Factor Analysis

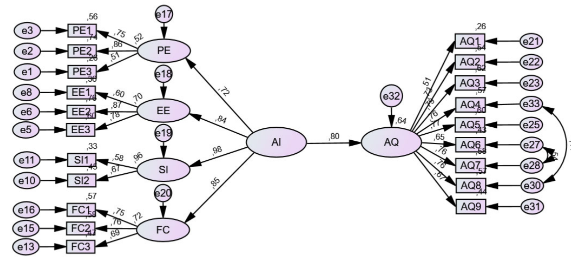

Fig. 3. Structural Equation Modelling

4.3. Structural equation modeling (SEM)

Structural equation modeling (SEM) was used to test hypothesis, specifically the ´path analysis' method; one of the structural equation modeling methods, as in Figure 3 and Table 4. The study discovered the following:

There is a significant statistical effect for Artificial Intelligence (AI) on the Audit Quality (AQ), which confirms the acceptance of (H1) **.**

Table 4
Regression Weights

Hypothesis			Standardized Regression Weights β	C.R. t-value	P-value	Hypothesis Supported?
H1 Audit Quality	←	Artificial Intelligence	0,800	4,544	***	Supported

Note **, p-value < 0.05; ***, p-value < 0.001. Significant at the 0.05 level.

4.4. Multi-group analysis

To examine whether or not the participant's types of job (auditing office, SMEs) affected the study hypothesis, SEM and a multi-group analytic approach were used as assessment tools. Therefore, data were divided into groups for auditing offices (40) and SMEs (80). To find any changes, the model trajectories of the two separate groups were compared. The variance between the whole structural models of the two groups under study can be learned through a χ2 difference test (auditing office vs. SMEs). Concerning the results, it is possible that one or more of the regressions between the two groups under investigation are not equal. The precise differences between the regressions along the path to each group, however, are not supported by the χ2 difference test. As a result, two groups were created in the AMOS v.26 graphics for each type of task to evaluate the variations in each route (hypothesis). For each type of employment, two categories were created in the AMOS v.26 graphics: one for auditing offices (which had a total of 40 participants) and another for SMEs (which had a total of 80 participants). Each regression was given a specific name for the test's purposes. Bootstrapping was used during the study to produce the confidence interval between the two tested groups. Table 5 shows that several important distinctions were emphasized for each group.

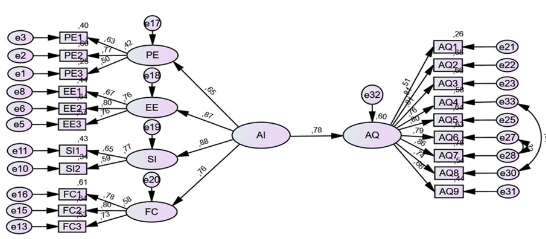

Fig. 4. SEM Multi-group analysis (SMEs Model)

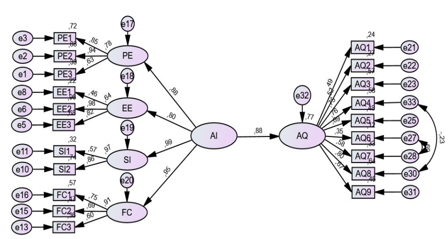

Fig. 5. SEM Multi-group analysis (Auditing office Model)

Table 5
SEM Multi-group analysis— (auditing office, SMEs)

Hypothesis			groups	Standardized Regression Weights β	C.R. t-value	P-value	Critical Ratios for Differences	Hypothesis Supported?
H1 Audit Quality	←	Artificial Intelligence	SMEs	.776	3.226	.001	-1.251	Not Supported
			auditing office	.876	3.011	.003		

Note **, p-value < 0.05; ***, p-value < 0.001. Significant at the 0.05 level.
Critical Ratios for Differences > 1,96 Significant**.**

The impact of AI on audit quality was found to be favorable and significant in both SMEs and auditing office groups; with no significant variations in Critical Ratios for the observed differences between the two, according to the results of the multi-group research**.**
In terms of the effects of AI on audit quality, the results of the study did not reveal any appreciable differences between the SMEs and auditing office groups. Which means that the second hypothesis H2 is not supported.

5. Discussion

There is a perception that utilizing AI helps to improve audit quality by external auditors and accountants who work for both Saudi SMEs concur that the hypothesized use of AI technologies and systems in auditing identifies and helps to spot instances of potential fraud and dangers. The study's results are also endorsed by the literature, according to Abdolmohmmadi (1991), which focuses on the application of AI to auditing. AI has a mixed effect on 'participants' decision-making that is studied during audit responsibilities that are pertinent to each of the audit duties and activities. Also, Knechel et al. (2008) show all SME commercials in Finland are required to undergo a financial statement audit, and as the business grows drives the need for a higher-quality auditor. Using the technology acceptance model (TAM), Huang et al. (2008) found organizational support and system quality are now factors that have an improved impact on perceived utility and usability. By using expert systems, Sánchez-Medina et al. (2019) findings showed that auditors became more likely to disclose going-concern uncertainties in the bankruptcy process in Spain SMEs, which influences audit quality. Also, Puthukulam et al. (2021) found professional skepticism and professional judgment have a substantial beneficial link with AI and auditing techniques. To increase auditing quality, AI and ML must be used in conjunction with human interaction. Also, Noordin & Hussainey (2022) found the role that AI plays in improving audit quality from the perspective of external auditors. Hassan (2022) added support to the 'study's findings by highlighting 'AI's beneficial effects on quality auditing. Artificial thinking could lead to several potential improvements in examining interactions, such as increased effectiveness and precision. Artificial perception can help automate certain tasks, like the passage and information analysis, which will increase accuracy and speed up the evaluation procedure.

Based on the findings of the hypothesis testing, H2 was verified; The perceived contribution of AI usage to audit quality significantly differs between external auditors and accountants in SMEs in the Kingdom of Saudi Arabia. According to the findings, there is no discernible difference in how external auditors and accountants in Saudi SMEs assess the use of 'AI's improvement of audit quality. The findings of earlier research by Chung & Narasimhan (2001), which show that both types of respondents view the small limited company audit as desirable, especially when considering the increased benefits it offers, provide credence to this. Also, Noordin & Hussainey (2022) discovered that there is no statistically significant difference between local and international audit firms in terms of how they evaluate 'AI's contributions to audit quality. All audit firms, whether national or foreign, are seen to contribute to audit quality. Also, Fedyk et al.(2022) indicated that most but not all AI employees are male, are young, and have technical degrees. A centralized function of AI inside the company, with employees concentrated in a small number of teams and places. Improved quality is the main objective of applying AI in audits, followed by increased efficiency.

While Chung & Narasimhan (2001) that audit fees put small businesses in a difficult financial position because many of the users of their financial statements could not benefit financially from having them reviewed.

6. Conclusion

This study looked at how Saudi 'SMEs' external auditors and accountants perceived AI's contribution to audit quality. The study also sought to ascertain whether there were any appreciable differences between external auditors and accountants in Saudi SMEs on the perception of the use of AI contribution to quality auditing. The usage of AI in auditing businesses will be required. The responding auditors anticipate that the usage of AI will boost productivity and add interest to their work. Although the nature of auditing services may change, the core offering, namely confidence and assurance, does not. Although AI will support audits, the human agency will still be necessary. To ensure the validity and reliability of the questionnaire, the data were evaluated using a different statistical test. Exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and (SEM) were used to test hypothesis 1 and determine the perceived benefit of utilizing AI to audit quality. The significance of the differences in how external auditors and accountants are regarded to contribute in Saudi SMEs was tested using an independent sample multi-group analysis. Regardless of the sort of audit firm an auditor works for, the study's findings can be used to gauge how practitioners and researchers perceive the benefits of AI. This can help them adopt the technology and help auditors develop their technical abilities. This study provides light into the most beneficial AI applications that auditors working with SMEs believe should be developed and used. It demonstrates that these auditors will accept AI to a high degree. For accounting experts and corporate executives, the practical ramifications of these study findings are crucial. Managers in both the public and private sectors ought to think about the benefits and significance of implementing AI to increase productivity and quality of work.

The study's main limitation is represented in the study sample that obtained 120 replies, of which 40 were from audit firms and 80 were from accountants in Saudi SMEs in Al Riyadh city. Moreover, the study solely used the UTAUT model. Future studies might look at the perceived contributions of various policymakers using a bigger sample size, especially one that is global. Further testing is required to improve the generalizability of the created scale for how AI systems are judged to contribute to audit quality. Also, Further testing is required to improve the scale's generalizability for how AI systems are judged to contribute to audit quality.

There are several probable future changes that deserve more consideration in terms of their implications on the sector and their consequences on audit education. Auditing instructors would need to update their curricula and stay current on advancements and effects associated with AI. To implement these improvements, future auditing education development would need to take an interdisciplinary approach. We advise looking at the contribution of AI from a different angle, not just in terms of audit quality but also in terms of various audit processes.

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