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Auditors' Opinion About AI and the Impact of AI on Audit Quality: A Study On Qualified Auditors in Africa[*]

Urich Joe Saly Lontsi [1]
Doğuş Ektik[2]

Abstract

The purpose of this study is to ascertain the opinions of African certified auditors on the use of artificial intelligence in auditing systems and the implications for audit quality. Artificial intelligence innovation has brought about significant improvements in the inspection industry, such as enhanced capacity for making decisions, reduced expenses, and increased efficiency. The investigation looks at a variety of AI-related topics, keeping in mind its uses for audits, ethical reflections, and barriers to widespread AI acceptance in Africa. A mixed methods approach was employed to coordinate the gathering and analysis of both quantitative and subjective data. To get data about planned research questionnaires was sent out to a specified irregular sample of 400 qualified auditors from different African nations. Study's research technique makes use of Cronbach's Alpha, one-way ANOVA, factor analysis, and descriptive analysis. Thematic investigation was used to hunt out typical subjects, and results cross-checked against quantitative data. The results demonstrate that while auditors generally support artificial intelligence, they also raise concerns about moral dilemmas and the need for appropriate training and background before working with artificial intelligence systems. Questionnaires sent to auditors from various age groups and educational backgrounds are crucial for the audit method, which provides a thorough understanding of their viewpoints. In general, the evaluation provides insightful information on the perception of artificial intelligence in the African audit sector and identifies fundamental areas that require further development in order to fully comprehend its potential advantages.

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[1] Graduate Student, Istanbul Aydın University, Institute of Graduate Studies, Accounting and Auditing (English), Istanbul, Turkey, urichjoe@yahoo.com, https://orcid.org/0009-0006-9483-7371
[2] Asst. Prof. Dr., Istanbul Aydin University, Faculty of Economics and Administrative Sciences, Accounting and Financial Management, Istanbul, Turkey, dogusektik@aydin.edu.tr, https://orcid.org/0000-0001-7095-6364

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Denetçilerin Yapay Zekâ Hakkındaki Görüşleri ve Yapay Zekânın Denetim Kalitesi Üzerindeki Etkisi: Afrika'daki Nitelikli Denetçiler Üzerine Bir Araştırma *

Urich Joe Saly Lontsi [1]
Doğuş Ektik [2]

Özet

Bu çalışmanın amacı, Afrikalı sertifikalı denetçilerin denetim sistemlerinde yapay zekâ kullanımı ve bunun denetim kalitesi üzerindeki etkileri hakkındaki görüşlerini tespit etmektir. Yapay zekâ inovasyonu, denetim sektöründe karar verme kapasitesinin artması, maliyetlerin azalması ve verimliliğin artması gibi önemli gelişmelere yol açmıştır. Araştırma, yapay zekânın denetimlerde kullanımını, etik yansımalarını ve Afrika'da yapay zekânın yaygın olarak kabul edilmesinin önündeki engelleri göz önünde bulundurarak yapay zekâ ile ilgili çeşitli konuları incelemektedir. Çalışmada hem nicel hem de nitel verilerin toplanması ile analizi tamamlamak için karma yaklaşım kullanılmıştır. Planlanan araştırma hakkında veri elde etmek için farklı Afrika ülkelerinden 400 nitelikli denetçiden oluşan belirli bir düzensiz örnekleme anketler gönderilmiştir. Çalışmanın araştırma tekniği Cronbach's Alpha, tek yönlü ANOVA, faktör analizi ve betimsel analizden yararlanmaktadır. Tipik konuları ortaya çıkarmak için tematik araştırma kullanılmış ve sonuçlar nicel verilerle çapraz kontrol edilmiştir. Sonuçlar, denetçilerin genel olarak yapay zekâyı desteklemekle birlikte, ahlaki ikilemler ve yapay zekâ sistemleriyle çalışmadan önce uygun eğitim ve arka plan ihtiyacı konusunda endişelerini dile getirdiklerini göstermektedir. Çeşitli yaş gruplarından ve eğitim geçmişlerinden denetçilerle yapılan anket, bakış açılarının kapsamlı bir şekilde anlaşılmasını sağlayan denetim yöntemi için çok önemlidir. Genel olarak değerlendirme, Afrika denetim sektöründeki yapay zekâ algısı hakkında aydınlatıcı bilgiler sunmakta ve potansiyel avantajlarının tam olarak kavranması için daha fazla geliştirilmesi gereken temel alanları belirlemektedir.

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* Bu çalışma İstanbul Aydın Üniversitesi, Lisansüstü Eğitim Enstitüsü, Muhasebe ve Denetimi Yüksek Lisans Programında Dr. Öğr. Üyesi Doğuş Ektik danışmanlığında yürütülen yüksek lisans tezinden türetilmiştir.

[1] Yüksek Lisans Öğrencisi, İstanbul Aydın Üniversitesi, Lisansüstü Eğitim Enstitüsü, Muhasebe ve Denetimi (İngilizce), İstanbul, Türkiye, urichjoe@yahoo.com, https://orcid.org/0009-0006-9483-7371
[2] Dr Öğr. Üyesi, İstanbul Aydın Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Muhasebe ve Finans Yönetimi, İstanbul, Türkiye, dogusektik@aydin.edu.tr, https://orcid.org/0000-0001-7095-6364

INTRODUCTION

Artificial intelligence is causing a big change in a few industries, like the audit sector. The application of artificial intelligence in information evaluation has led to remarkable advancements, such as enhanced critical thinking abilities, reduced expenses, and increased efficiency. In addition to assisting associations and auditors in making informed judgments, the analysis provides further understanding through which we may analyze the ways in which computational reasoning affects knowledge evaluation and gets ready for next developments.

Because of the expansion of businesses and the growth of the business community, financial advances are becoming more consistent. Every company strives to create its own frameworks based on strong principles and to continue operating indefinitely. An organization would benefit from having strong internal control and accounting systems that set it apart from competitors at this point if it wanted to be taken seriously. An association needs a quality audit framework in order for its accounting and internal control systems to function flawlessly. At this stage, the significance of examiners and evaluators becomes clear.

Research Objectives

The following are the research objectives:

- Examine competent auditors' attitudes and views on artificial intelligence (AI) in Africa as it relates to audit procedures.
- Examine how competent auditors in Africa view the influence of AI on audit quality, taking into account variables such audit method dependability, effectiveness, and efficiency.
- Determine the potential and difficulties that come with incorporating AI into audit procedures in Africa, taking into account concerns about data quality, technology infrastructure, and legal compliance.
- Analyze how prepared African auditors are to adjust to the changing environment of AI-driven auditing and pinpoint possible opportunities for professional growth and capacity improvement.

Problem Statement

Even while artificial intelligence, is becoming more and more common in many industries, qualified auditors in Africa are still unsure of what this implies for audit quality. Due to this knowledge gap, it is difficult to effectively use simulated intelligence tools and advancements in order to improve review processes and uphold high standards of value confirmation. The auditors' perspectives on artificial intelligence and its implications for review quality in the African context must be examined in order to solve this crucial problem.

Research Hypothesis

H1: There is a significant difference in the perceived ease of use between the types of AI (Assisted/ Augmented/ Autonomous).

H2: There is a significant difference in the perceived usefulness between the types of AI (Assisted/ Augmented/ Autonomous)

H3: There is a significant difference in the perceived contribution between the types of AI (Assisted/ Augmented/ Autonomous)

Theoretical Framework

According to Enholm, Papagiannidis, Mikalef and Krogstie (2022), AI is essential for organizations and foundations. It's unclear what kinds of company benefits might be anticipated because of artificial intelligence advancements and how they could elevate businesses (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022). Developments in artificial intelligence enable organizations to enhance human labor or automate procedures for internal and external applications. When artificial intelligence is employed internally, it refers to the use of computer intelligence to improve internal business operations without having to interact directly with customers (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022). Artificial intelligence applications may provide value to businesses by increasing corporate efficiency, cutting costs, and generating revenue, according to Alsheibani, Messom and Cheung (2020). That is why the development of AI tools are becoming more and more gigantic. The lack of trust in AI tools discourages auditors from auditing through AI and instead they audit around it by reviewing the outputs the tools generate.

Abdollahi, Pitenoei and Gerayli (2020) described audit quality as a way of making sure that the financial statements audited are free from any mistake thereby making sure it aligns with the main objective of an audit which is to obtain reasonable assurance that financial statements are free from any sort of irregularities.

It is good to note that studies like Lawal, Akintoye, Abiodun and Olawumi (2020) and Agur, Peria and Rochon (2020) sees audit quality as subjective and personal although other studies like Alawaqleh & Almasria (2021) considers audit quality as highly influenced by many other factors like audit independence, the audit fee, the size audit firm and many others.

As mentioned by Klovienė and Dagilienė (2019), AI had previously been expressed as a machine that displays unusual human cognitive skills associated with problem solving and learning in an astonishing and precise process with a well-timed reporting.

Looking at this from the financial reporting (auditing) perspective, AI is considered as a data mining tool which is logically structured to generate reliable and accurate forecasts. It facilitates the processing and automation of the authorization of documents to ameliorate internal accounting reporting and processes. AI tends to particularly leverage programmed and computerized algorithm to easily identify and comprehend patterns and irregularities within data sets, thereby making sure auditors can identify specific areas of risks more efficiently and execute many other auditing and accounting processing tasks at an unrivalled speed. Dessureault and Benito (2012) point out that it can duplicate or recreate unquestionable facets of human behaviors and intelligence. Giehl, Göcke, Grosse, Kochems, & Müller-Kirchenbauer (2020) pined out that AI has the ability to; improve audit quality, thereby amplifying or strengthening the quality of financial reporting using AI tools.

Nevertheless, there are lot of challenges related to the developments of AI tools to be used in auditing. The most important challenges related to our area of study (auditing) are the way these tools are used, data privacy issues, the fear auditor's overreliance on such tools, fear AI's biasness, the constant need of AI guidance and most especially the issues of transparency and explainability thereby causing a lack of trust in Artificial Intelligence tools for auditing which on the other hand serves as a discouragement to auditors from using them when performing auditing, they rather perform audit around it by making sure they review all the outputs generated by these AI tools (Kokina, Blanchette, Davenport, & Pachamanova, 2025).

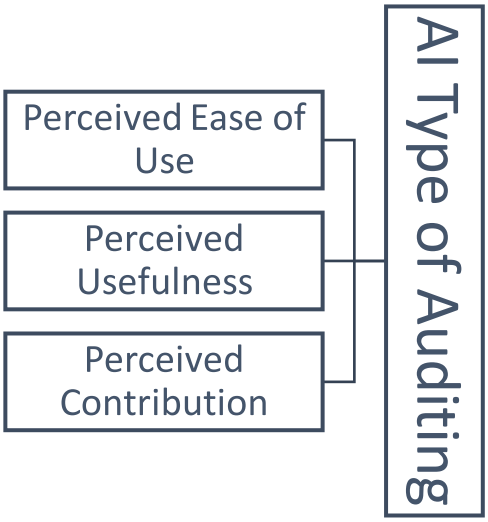

Figure 1: The Relationship Between the Types of AI and Auditing
Source: Albawwat & Frijat, 2021

The table above depict or illustrate the various subtitles used in our questionnaires to investigate what certified auditors in Africa think about Artificial Intelligence and to what extern do they think Artificial Intelligence can be of great help to them on their daily activities at the workplace. From investigating on if they think Artificial Intelligence could be easily used by them in the profession, the level of usefulness Artificial Intelligence could be to the auditing profession as a whole regarding the perceived usefulness. Lastly, the perceived contribution simply seeks to understand the level of contribution Artificial Intelligence has as far as the auditing profession is concerned.

In order to come up with the results of this research, the study will be making use of the reliability test (Cronbach's Alpha) which is a method that examines the internal consistency of a set of test items or how closely related a set of items are as a group, the PCA (Principal Component Analysis) extraction method which is indeed a powerful statistical technique used to simplify and interpret complex data set. Without forgetting the KMO and Bartlett's Test used to make sure the data set are 100% suitable for research and findings.

In the study that will be talking more about this in the result and analysis part where the results of the study shall be well and meticulously explained.

LITERATURE REVIEW

Accounting firms are using artificial intelligence, more and more in their auditing and advisory services. These companies list a number of benefits that come with using simulated intelligence, such as reduced time investment costs, faster information processing, more accuracy, deeper insights into business operations, and improved customer service. Those that embrace electronic intelligence, a cutting-edge invention aimed at imitating human cognitive abilities and decision-making, will get the upper hand. The Big Four, or the massive accounting businesses, are currently embracing simulated intelligence and want to use it for various objectives going forward, such as risk assessments for review scheduling, exchange testing, examination, and review work-paper generation. Nevertheless, as additional benefits and applications of artificial intelligence in assessment are discovered, people are becoming more conscious of the possibility of unforeseen consequences (Munoko, Liburd, & Vasarhelyi, 2020).

In a review of the work produced by the Dhaka-based Bangladeshi institution. According to Hasan (2022), even with the potential disruption artificial intelligence can bring to the sector going forward, it is highly unlikely that the need for human expertise will completely disappear. Thus, the general public should embrace computer-based intelligence while maintaining efficacy and value as our primary goals (Hasan, 2022).

According to Zemankova (2019) analysis, AI in accounting and audit demonstrates extraordinary commitment for increasing productivity, reducing errors, and freeing up more time for bookkeepers and evaluators to focus on important and complex tasks rather than routine, rule-based work (Zemankova, 2019).

There are still many areas of artificial intelligence that need to be investigated further, such as the study of the advantages and disadvantages of AI initiatives, the degree to which audit judgment may be automated, and the suitability of audit populations as deep learning samples (Issa, Sun, & Vasarhelyi, 2016).

In Africa, a major barrier to the recognition and use of human intelligence is a lack of computer literacy. With only a fraction of the global average for the acceptance of computer skills in all domains, Sub-Saharan Africa is home to the fewest highly educated individuals worldwide (Madden & Kanos, 2021). “The Fate of Work in Africa 2021” a World Bank study, indicates that people in South Africa, Kenya, and Nigeria have higher levels of computerized education than those in the rest of sub-Saharan Africa (Choi, Dutz, & Usman, 2020). In response to the UN's Maintainable Advancement Objectives, the World Bank launched the Computerized Economy for Africa (DE4A) initiative, which aims to enable every African person, business, and state to access computerized innovation by 2030 (World Bank, 2021). Building blocks for an automated economy across Africa promise to support economic growth and reduce poverty by boosting the enterprise of young adults, increasing the productivity and yields of horticulture, and changing the labor force by providing more opportunities for women to enter the workforce (World Bank, 2021).

Even if some of the data in this section may appear depressing, it's important to understand the main, proven factors that have contributed to these results. Due in large part to African legislators' lack of interest in the foundation meant to boost advanced economies, computer proficiency has typically not expanded.

With the assistance of multilateral organizations and international financial institutions, nations such as Mozambique and Rwanda have proactively started to develop action plans to achieve digital transformation (World Bank, 2021). Large innovative companies have recently realized how important it is to equip local labor forces with computer skills training. In order to significantly advance the last choice country's digital economy, Microsoft and the Nigerian government formed a cooperative endeavor in May 2021 (Microsoft, 2021). This organization hopes to assist Nigeria's transition to a modern economy by demonstrating a strong interest in web foundation, training 5 million people nationwide in computer skills, creating cloud-based devices to combat defilement, and using artificial intelligence to protect social legacy.

Given that companies like Microsoft, Twitter, IBM, Facebook, and Google have historically had such strengths on the continent of Africa, Microsoft's commitment can help evaluate the regional narratives and components observed in many economic sectors, such as horticulture and mining. That being said, they are not exempt from criticism or anxiety around their existence. Big Tech's existence in Africa is mostly due to its imposing business methods, financial resources, and desire to maintain power above all things. It is not the legend that Africa needs to look up to.

AI Technology in the Audit Sector

Artificial Intelligence (AI) in the context of audit procedures refers to the deployment of cutting-edge computing technologies that mimic human intelligence to improve a number of audit process features (Issa, Sun, & Vasarhelyi, 2016). Artificial Intelligence (AI) in auditing refers to the creation and application of computer systems that can execute activities that auditors typically do in order to increase audit processes' overall efficacy, accuracy, and efficiency. Using machine learning algorithms, natural language processing, and data analytics, for example, may be used to examine vast amounts of financial data, spot trends, spot abnormalities, and offer insights that help with better decision-making in the auditing field. The incorporation of artificial intelligence (AI) technology into audit procedures seeks to optimize workflows, minimize human labor, and augment the capacity to unearth insights from intricate datasets, culminating in an improvement of audit quality and comprehensiveness (Dagunduro , Falana, Adewara, & Busayo , 2023).

Responsible AI in Africa

The Global North has essentially served as the center of generated by human logic, events, and mixture since its inception. This power concentration is directly related to the frontier history of asset extraction from the Global South, which deprived these countries of their independence and industrialization potential. Because of this inaccuracy, applications of artificial intelligence have come to see it as more difficult to succeed in such circumstances — that is, to operate in a manner that does not exacerbate already-existing variances.

The acceptance and use of artificial intelligence depends on a number of factors, such as the availability of a trained local labor force capable of supporting these arrangements, enough infrastructure to support mathematically complex calculation preparation, delegate datasets, legislative support and guidelines to oversee the appropriate and impartial application of these innovations, free and shared foundations, and legislators who protect against harmful applications and uphold liability and responsibility.

METHODOLOGY

Research Strategy

For the examination, a mixed methods approach will be employed to coordinate the gathering and analysis of both quantitative and subjective data. In order to get data on socioeconomics, perceived usefulness and clarity of goal, dedication to quality review, and limitations in artificial intelligence applications, a planned research will be sent out to a specified irregular sample of 410 qualified auditors from different African nations. The information research technique will often make use of factor analysis, One-way ANOVA which is a simply used to examine and determine if there are any statistically significant differences among the means of more than two independent groups, Cronbach's Alpha (this is a way of evaluating reliability by simply comparing the amount of shared variance and or covariance among the items which makes an instrument to the amount of overall variance), KMO and Bartlett's Test and descriptive analysis. Thematic investigation will be used to hunt out typical subjects, and results will be cross-checked against quantitative data. A few moral difficulties are obtaining informed permission, maintaining privacy, and safely preserving information. During the three-month focus period, specific tasks related to literature, study schedule, data collection, analysis, and report writing will be scheduled.

Targeted Population

According to (Lancaster, 2005), population refers to "the complete set of items or topics under inquiry". The total population consists of approximately 400 of 410 qualified auditors from different African nations. During the target population selection, most specifically 4 African nations selected which are, Nigeria (this country was selected because it is the most populated country in Africa and therefore, we couldn’t perform at research without taking this country into account. Also, part of the targeted population is from Kenya, this is because Kenya is the country with the highest number of technological advancements Invalid source specified. Another part of targeted population is from Cameroon; this is mainly because Cameroon is the only bilingual African nation and as such uses both the French and English standards in auditing. Lastly, some qualified South African auditors were equally considered when sending out the questionnaires because South Africa is the home of the largest bank in Africa Invalid source specified. and therefore should not be left aside.

Sampling Population

In addition almost 400 number of samples were selected out of 410, to test the result in the return of a floated questionnaire in sample population of 1,230,004. In this study, samples were recruited by implying the qualitative method technique.

Research Instruments

We will interact with them through questionnaires so that information may be gathered. The data collection method will involve using closed-ended questionnaires, which participants in the study will be asked to fill out. The questionnaire will be designed using a five-point Likert scale that measures Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree. There are two sections to the questionnaire: the first asks questions concerning the personal details of the respondents, and the second part asks questions concerning the study constructs. The instrument was specifically chosen since it solicits the respondents' opinions and gives them the opportunity to draw on their experience to offer a range of facts.

RESULT AND ANALYSIS

Reliability Test

Table 1: *Reliability Test*

Construct	Cronbach’s Alpha	Number of Items
Perceived Ease of Use	.865	6
Perceived Usefulness	.842	6
Perceived Contribution to Audit Quality	.760	11

The table examines the reliability of three important constructs: perceived ease of use, perceived usefulness, and perceived contribution to audit quality. The reliability of each construct is evaluated using Cronbach's Alpha, which evaluates the internal consistency of the items inside each scale.

The perceived ease of use Cronbach's Alpha score of 0.865 indicates a high degree of reliability. This demonstrates the significant relationship and reliable findings produced by the six variables that were used to quantify this construct. Similar to perceived usefulness, which has excellent internal consistency across all six measures, perceived usefulness has a Cronbach's Alpha of 0.842. Both of these constructs exhibit dependable quality, indicating that the items accurately reflect the expected perceptions.

However, the perceived contribution to audit quality, which is dependent on eleven variables, has a Cronbach's Alpha of 0.760. Although this score is lower than the other two constructs, it nevertheless meets the widely acknowledged reliability criteria, indicating that the scale is sufficiently consistent. All three of the constructs in the table rise over the Cronbach's Alpha threshold of 0.7, which is generally regarded as acceptable. This indicates the reliability of the scales used in the review

Factor Analysis

We shall be making use of the PCA (Principal Component Analysis) method. This is a powerful statistical technique which is used to simplify and interpret complex data set. It is a dimensionality reduction method that transforms a large set of correlated variables into a smaller set of uncorrelated variables usually known as principal component. Thereby eliminating irrelevant data.

KMO and Bartlett's Test

Table 2: *KMO and Bartlett's Test*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.936
Bartlett's Test of Sphericity	Approx. Chi-Square	3457.485
	df	253
	Sig.	.000

Two important prerequisites for us to conduct factor analysis is the KMO and Bartlett's Test. Starting with the KMO (Kaiser-Meyer-Olkin) measure of sampling adequacy, if factor analysis is suitable for our dataset, then the KMO should show a sample of number greater than .7, if the KMO is less than .7, it is advisable not to perform factor analysis. This therefore means that our dataset is suitable for factor analysis because as can be seen in table 4, our Kaiser-Meyer-Olkin Measure of Sampling Adequacy is .936, meaning our data set has sufficient correlation.

The second important criteria to check whether our dataset is suitable for factor analysis is the Bartlett's Test of Sphericity. This is mainly used to confirm whether the correlation matrix of the variables in our dataset diverges significantly from the identity matrix. In other words, it provides information as to whether the correlations in the dataset are strong enough to use a dimension-reduction technique like the principal component analysis to be used in this section. As we can confirm in table 4 above, the Bartlett's Test of Sphericity has a Sig (P-value) of .000 which is clearly lower than 0.05, therefore we can reject our null hypothesis and conclude that the correlation matrix is not an identity matrix and thus can be dimensionally reduced with the PCA (Principal Component Analysis).

Total Variance Explained and Scree Plot

For us to know the total number of factors to be retained for future purposes or for a later expansion of the research, we look at the total variance explained table and the scree plot figure.

Table 3: *Total Variance Explained*

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.288	36.033	36.033	8.288	36.033	36.033	4.687	20.377	20.377
2	1.424	6.193	42.226	1.424	6.193	42.226	3.170	13.783	34.160
3	1.218	5.295	47.521	1.218	5.295	47.521	2.797	12.161	46.321
4	1.028	4.468	51.989	1.028	4.468	51.989	1.304	5.669	51.989
5	.957	4.161	56.150						
6	.924	4.018	60.168						
7	.853	3.708	63.876						
8	.819	3.561	67.437						
9	.746	3.243	70.680						
10	.708	3.078	73.758						
11	.646	2.808	76.566						
12	.612	2.662	79.228						
13	.591	2.570	81.798						
14	.551	2.395	84.192						
15	.544	2.366	86.559						
16	.494	2.147	88.706						
17	.470	2.045	90.751						
18	.439	1.907	92.658						
19	.396	1.720	94.378						
20	.372	1.616	95.994						
21	.362	1.574	97.568						
22	.295	1.282	98.850						
23	.264	1.150	100.000						
Extraction Method: Principal Component Analysis.									

As can be seen in the above table, only 4 components will be retained from the available variables because only four of them have a total Initial Eigenvalues of greater than one. Therefore, we will be selecting a 4 components solution. Component 1 for example has a total initial eigenvalue of 8.288 same as the extraction sums of squared loadings total, which is greater than one and hence should therefore be retained. So does the same holds for component 2, 3, and 4 with a total initial eigenvalue of 1.424, 1.218, and 1.028 respectively.

Also, the percentage of variance for both the initial eigenvalues and extraction sums of squared for component 1 is 36.033. This means that component one explains or could cover 36.033% of variation individually in the dataset. Same as the percentage of variance for the initial eigenvalues for component 2, 3, and 4 individually explains the variation percentage each component covers (6.193% for component 2, 5.295% for component 3, and 4.468% for component 4 individually).

If we add up the % variances for component 1 to 4, we will realize that it explains 51.989 percent (52%) of variation in the dataset. Meaning the first 4 components are able to account for 52% of the variation in the total dataset while the rest of the 19 components all together accounts for less than 50% of variation in the overall dataset. Due to the negligibility of their contributions, we can ignore the remaining 19 components (that is from component 5 to 23) and retain only the first 4. The above table could be graphically explained with a Scree Plot as seen below;

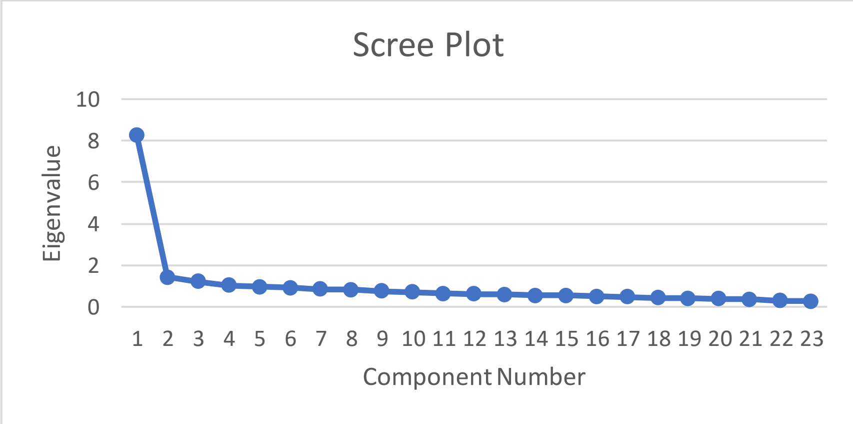

Figure 2: Scree Plot

We can easily see that after component 4, where the eigenvalues begin to fall below 1.

Rotated Component Matrix

Table 3: *Rotated Component Matrix*

	Component			
	1	2	3	4
I would find AI systems and tools in auditing to be flexible to interact with	.757			
My interaction with AI systems and tools in auditing would be clear/understandable	.750			
It would be easy for me to become skillful with AI systems and tools in auditing	.748			
I would find it easy to get AI systems and tools to do what I want it to do in auditing	.714			
I would find AI systems and tools in auditing easy to use	.667			
Learning to operate AI systems and tools in auditing would be easy for me	.563			
Using AI systems and tools in my future auditing job would enable me to accomplish tasks more quickly	.528			
I would find AI systems and tools useful in my future job in auditing	.518	.355		
Using AI systems and tools would improve my future job performance in auditing	.307	.697		
Using AI systems and tools in my future auditing job would increase my productivity	.430	.644		
Using AI systems and tools would enhance my effectiveness of the job in auditing	.478	.590		
Using AI systems and tools in auditing will enable ongoing risk assessment throughout the audit process		.573	.447	
Using AI systems and tools in auditing will facilitate robust risk assessment through the analysis of entire populations		.564	.349	
Using AI systems and tools would make it easier to do my future job in auditing	.464	.502		
Using AI systems and tools in auditing will deepen my understanding of the entity and its processes		.405		
Using AI systems and tools in auditing will enable the independent reperformance of complex calculations and modelling			.678	
Using AI systems and tools in auditing will identify unusual patterns and exceptions that might not be discernible using more traditional audit techniques	.302		.595	
Using AI systems and tools in auditing will enable me to perform tests on large or complex datasets where a manual approach would not be feasible			.592	
Using AI systems and tools in auditing will improve consistency and central oversight in group audits			.586	
Using AI systems and tools in auditing will facilitate the focus of audit testing on the areas of highest risk through stratification of large populations		.420	.561	
Using AI systems and tools in auditing will aid my professional skepticism				.647
Using AI systems and tools in auditing will identify instances of potential fraud				.595
Using AI systems and tools in auditing will automate routine audit processes and procedures, allowing more time to focus on areas of significant judgment	.312	.350	.358	-.425

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

This is a matrix that explains the loadings of each variable on the principal component after rotation. Rotations simplifies the whole interpretation of the components by easily grouping similar variables together. The blank space that can be seen in the above table does not mean that there are no numbers (component/factor loadings or correlation values) but simply that the numbers are too small (we used a minimum number of .3, that is why all the other brackets have values greater than .3). Component loadings represent the correlation between each variable and the principal component. The loadings therefore range from -1 which indicate perfect negative correlation to 1, indicating perfect positive correlation. Therefore, a loading value of closed to 0 indicates little correlation between the variables and the component.

As can be seen in table 6, the first component has a loading of .757 with the first variables, .750 with the second variables, .748 with the third variable, .714 for the fourth variable and so on. You can realize that as we go down to subsequent variables, the numbers start declining.

Correlations matrix of the extracted four components

Table 4: *Correlations*

		REGR factor score 1 for analysis 1	**REGR factor score 2 for analysis 1**	**REGR factor score 3 for analysis 1**	**REGR factor score 4 for analysis 1**
REGR factor score 1 for analysis 1	Pearson Correlation	1	.000	.000	.000
	Sig. (2-tailed)		1.000	1.000	1.000
	N	400	400	400	400
REGR factor score 2 for analysis 1	Pearson Correlation	.000	1	.000	.000
	Sig. (2-tailed)	1.000		1.000	1.000
	N	400	400	400	400
REGR factor score 3 for analysis 1	Pearson Correlation	.000	.000	1	.000
	Sig. (2-tailed)	1.000	1.000		1.000
	N	400	400	400	400
REGR factor score 4 for analysis 1	Pearson Correlation	.000	.000	.000	1
	Sig. (2-tailed)	1.000	1.000	1.000	
	N	400	400	400	400

This is the final step to factor analysis as we need to confirm that the previously extracted 4 factors (components) are suitable for our data set. Looking table 7, along the column we have the factor scores same as along the rows where the SPSS reports the Pearson Correlation significance value. It is good to note that any factor correlated with itself will give a value of one as can be seen where factor one and itself meet, where factor 2 and itself meet and so on. Our main interest here are the Pearson Correlation values for factor 1 and other factors. For example, the Pearson Correlation score for factor 1 (in the first row above) and that of factor 2 gives a score of .000. Same as that of factor 3 and 4 in the columns, while their significance (2-tailed) is 1 for the 3 factors. The same goes with factor 2 (in the rows) and that of factor 1 in columns which gives a Pearson Correlation of .000 as well as factor 3 and 4 in the rows. The N shows the sample size which is 400. The above table simply shows that there is an uncorrelated relationship between the 4 factors, indicating that the new four components that we have derived from the data are uncorrelated. Thus, we can use the above factors if performing any advanced analysis as independent variables instead of the large number of variables previously obtained from the questionnaires because these components respect one of the most important assumptions of linear regression which state that there should not be any multicollinearity problem or in other words the independent variable should be completely uncorrelated.

Significance

Table 5: *Significance*

Type of AI	Other AIs	Mean Difference	Sig.
Perceived Ease of Use			
Assisted AI Systems	Augmented AI Systems	0.04717	0.892
	Autonomous AI Systems	-0.00228	1.000
Augmented AI Systems	Assisted AI Systems	-0.04717	0.892
	Autonomous AI Systems	-0.04945	0.898
Autonomous AI Systems	Assisted AI Systems	0.00228	1.000
	Augmented AI Systems	0.04945	0.898
Perceived Usefulness			
Assisted AI Systems	Augmented AI Systems	0.10289	0.560
	Autonomous AI Systems	0.04782	0.900
Augmented AI Systems	Assisted AI Systems	-0.10289	0.560
	Autonomous AI Systems	-0.05508	0.871
Autonomous AI Systems	Assisted AI Systems	-0.04782	0.900
	Augmented AI Systems	0.05508	0.871
Perceived Contribution to Audit Quality			
Assisted AI Systems	Augmented AI Systems	0.03930	0.862
	Autonomous AI Systems	-0.08679	0.502
Augmented AI Systems	Assisted AI Systems	-0.03930	0.862
	Autonomous AI Systems	-0.12609	0.259
Autonomous AI Systems	Assisted AI Systems	0.08679	0.502
	Augmented AI Systems	0.12609	0.259

The findings of a one-way ANOVA used to assess the differences in perceived utility, perceived ease of use, and perceived contribution to audit quality among three categories of AI systems—Assisted AI Systems, Augmented AI Systems, and Autonomous AI Systems—are displayed in the table. When it came to perceived usability, the mean difference between the various types of AI systems was not very great. More specifically, the difference between Assisted AI Systems and Augmented AI Systems was 0.04717, the difference between Assisted AI Systems and Autonomous AI Systems was -0.00228, and the difference between Augmented AI Systems and Autonomous AI Systems was -0.04945. Nevertheless, the p-values ranged from 0.892 to 1.000, indicating that consumers did not perceive any appreciable variations in the ease of use among three types of AI.

In the same manner, there were not very large mean variations in perceived usefulness. augmented and assisted artificial intelligence systems The difference between assisted and augmented AI systems was 0.10289; the difference between autonomous and augmented AI systems was 0.04782; and the difference between autonomous and augmented AI systems was - 0.05508. P-values ranging from 0.560 to 0.900 indicated that these differences were not statistically significant. This suggests that consumers believed the three AI systems to be roughly equal in terms of utility.

Finally, the mean difference for the perceived audit quality contribution was as follows: the difference between autonomous and augmented AI systems was 0.12609, the difference between assisted and autonomous AI systems was 0.08679, and the difference between augmented and autonomous AI systems was 0.03930. These increases were not very large, with p-values ranging from 0.259 to 0.862, suggesting that users believed various artificial intelligence frameworks contributed to review quality in roughly the same ways.

Everything considered, the one-way ANOVA results demonstrate that there are no statistically significant differences in the perceived usefulness, ease of use, or audit quality contribution of Assisted AI Systems, Augmented AI Systems, and Autonomous AI Systems. Customers often see these AI systems as almost the same in all of these areas.

Result Summary

Table 6: *Result Summary*

Type of AI	Other AIs	Sig.	Accepted/ Rejected
Perceived Ease of Use			
Assisted AI Systems	Augmented AI Systems	0.892	Rejected
	Autonomous AI Systems	1.000	
Augmented AI Systems	Assisted AI Systems	0.892	Rejected
	Autonomous AI Systems	0.898	
Autonomous AI Systems	Assisted AI Systems	1.000	Rejected
	Augmented AI Systems	0.898	
Perceived Usefulness			
Assisted AI Systems	Augmented AI Systems	0.560	Rejected
	Autonomous AI Systems	0.900	
Augmented AI Systems	Assisted AI Systems	0.560	Rejected
	Autonomous AI Systems	0.871	
Autonomous AI Systems	Assisted AI Systems	0.900	Rejected
	Augmented AI Systems	0.871	
Perceived Contribution to Audit Quality			
Assisted AI Systems	Augmented AI Systems	0.862	Rejected
	Autonomous AI Systems	0.502	
Augmented AI Systems	Assisted AI Systems	0.862	Rejected
	Autonomous AI Systems	0.259	
Autonomous AI Systems	Assisted AI Systems	0.502	Rejected
	Augmented AI Systems	0.259	

The one-way ANOVA results show that there is no real difference between the three types of AI systems (Assisted AI Systems, Augmented AI Systems, and Autonomous AI Systems) in terms of perceived usefulness, perceived ease of use, and perceived contribution to audit quality. Every comparison had p-values (significant levels) over the 0.05 threshold, indicating the rejection of any anticipated differences between these artificial intelligence systems.

P-values specifically fall between 0.560 and 0.900 for perceived usefulness and between 0.892 and 1.000 for perceived ease of use. Accordingly, the perceived audit quality contribution p-values vary from 0.259 to 0.862. Based on these results, the hypothesis which states that there are significant differences between the different types of AI systems—is rejected in all respects, indicating that most customers believe these frameworks to be almost comparable in terms of their usefulness, ease of use, and ability to improve audit quality.

CONCLUSSION

The analysis concludes that artificial intelligence innovation has great promise for improving audit quality by promoting efficiency, removing confusion, and providing a deeper understanding of organizational operations. Artificial intelligence, has the potential to advance information analysis, help with repetitive chores, and identify inconsistencies that human auditors would overlook. However, a number of challenges need to be resolved in order to successfully integrate AI into audits these issues include those related to framework, computer competency, morality, and a lack of skilled local artificial intelligence specialists. The handling of moral dilemmas that call for caution include information protection, algorithmic tendencies, and the acceptance of computer-based intelligence judgments. The study also highlights how important it is to provide auditors with the necessary training so they can effectively use artificially intelligent devices and provide a solid basis for artificial intelligence applications. Auditors acknowledge the anticipated benefits of artificial intelligence, but they also highlight the need of human knowledge in making well-informed decisions overall. The study argues that a balanced method that combines human talent with artificial intelligence innovation is necessary to further increase audit quality in Africa. This system makes sure that human auditors provide context and management-oriented information, while artificial intelligence handles repetitive and disorganized information tasks.

Future Work

Future studies should concentrate on analyzing the long-term effects of artificial intelligence reception in the audit sector, specifically with regard to ethical concerns and audit quality. It will need more time and thorough investigation to determine which artificial intelligence tools and processes perform best in various auditing scenarios. Research should also look at developing curriculum and enhancing infrastructure to support artificial intelligence use in Africa. This entails investigating concerted efforts with academic institutions to create a reservoir of intelligent artificial intelligence auditors and creating native artificial intelligence systems customized to the unique challenges of the African auditing environment. Further studies ought to examine how administrative systems contribute to ensuring that artificial intelligence is used carefully in auditing. Information security, responsibility, and the need to approve AI tools should all be covered by these organizations. Additional longitudinal research may provide light on how the usage of artificial intelligence evolves over time and what factors remain significant for audit professions and audit quality.

Limitations

The survey has a number of limitations, including its narrow geographic focus (Africa is the only continent it covers) and the possibility of responder bias because auditors may or may not be involved in artificial intelligence. Additionally, the investigation makes use of self-detailed data, which was unable to adequately handle the complexity of integrating AI into analysis techniques. Furthermore, the results cannot be applied to other areas or organizations, and the sample size is unlikely to be representative of all African inspectors. In order to synthesize the findings and propose a more comprehensive information on artificial intelligence's influence on audit quality, larger and more variable test sizes are anticipated for further research. It's also critical to investigate the viewpoints of several collaborators, including as administrative organizations, audit clients, and artificial intelligence makers, in order to fully understand the possibilities and challenges associated with artificial intelligence in assessing. By addressing these problems, research will proceed more thoroughly in the future and provide experts and decision-makers with more insightful information.

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