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THE EXTENT OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IMPACT ON AUDIT EVIDENCE-AN EXPLORATORY STUDY ON A SAMPLE OF AUDITORS AT THE UNIVERSITY OF MOSUL

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Abstract
Technological advancement has significantly influenced various industries, and one of them is auditing because artificial intelligence technologies are progressively used for multiple purposes. Key to the transformation of evidence collection and assessment is the promise that AI seemingly offers in this regard. This study is exploratory research which investigates the AI impact on audit evidence practices using a sample of auditors at University of Mosul. We use a mixed methods approach that includes qualitative interviews with auditors to understand their perceptions and experience working with AI-embedded tools, along with a broad quantitative survey designed to capture the ubiquity and types of various audit evidence gathering technologies.
50 questionnaires were distributed to the research sample consisting of auditors at the University of Mosul, and the SPSS statistical program was used to reach conclusions. Overall, our findings indicate that AI's adoption in auditing is still nascent and far from pervasive; however, it is already having an impact on how auditors deal with evidence. In particular, AI allows them to examine additional data sources at a scale unheard of before and assures the feasibility of continuous audits including identifying more anomalies prevalent in audit data points "Challenges, on the other hand, remain with respect to validating the dependability of such AI-produced audit evidence.
In twain subjects, this con-over presents a precious concomitatement to the escalating compute of elimination on the movables of AI in auditing. It provides an initial account of the current use of AI for audit evidence in a single university and link to explore later work on AI's transforming effects on exam practices. The findings of this research could be beneficial to accounting firms, regulators, and educators seeking to gain a better understanding of the potential opportunities and risks associated with AI in respect of audit evidence.

Keywords: artificial intelligence, audit evidence.

Introduction
In today's ever-changing environment, the use of artificial intelligence (AI) technologies is proving to be a game changer in modern audit methods and procedures that will change an

auditor’s perspective on how we approach our evidence. In a world that’s rapidly becoming more data driven, being able to analyze vast swaths of information efficiently and effectively is crucial. Hence, this exploratory study investigates the effect of AI technology on audit evidence based on a sample of auditors located at the University of Mosul in Iraq.

Audit work has been known for always depending on strict evidence examination that assures the integrity and reliability of financial statements or business processes. However, the old-fashioned way of collecting and studying audit evidence can be time-consuming, labor-intensive, and subject to human error (Issa et al., 2016).AI technologies, such as machine learning, natural language processing and data analytics, have the potential to totally change auditing procedures by improving efficiency of evidence analysis, increasing levels of accuracy and deepening the analysis according to a recent survey by the International Federation of Accountants IFAC (2021), the adoption of AI technologies in auditing is on the rise, with 62 percent of respondents using AI-driven tools for data analysis and risk assessment. Furthermore, an audit report issued by PwC (2020) suggests that AI-supported audit work processes can cut spent on menial tasks by up to 40%, leaving auditors free to concentrate on more important work and to provide fresher advice that adds value For the Audit profession in Iraq, the digital age has meant a major change in work content. It brings new technologies that can enhance the quality and effectiveness of audits.

This paper intends to fill the existing gap in auditing’s literature on how AI technology has changed audit evidence. For example, it aims to address what auditors (at university of Mosul) know and believe about these artificial intelligent technologies. We also hope that this study may be informative for auditors, as well as policymakers in Iraq and elsewhere by examining the extent to which AI technologies are employed at present, the issues raised upon their adaption or applied use in auditing activities, and what auditors see as advantages and disadvantages of such changes.

1.2 Problem Statement

The increasing sophistication of financial transactions, the sheer size of data being generated and received, as well as the demands for more effective and efficient audit process has remained challenging to auditors in Iraq. However, traditional audit practices and procedures may no longer be suitable to adapt to these changes. This could jeopardize the quality and reliability of the audits. To counterbalance the inherent challenges, the utilization and adoption of artificial intelligence technologies within the audit process appear to improve our ability to provide more sufficient and effective audit evidence through data collection, analysis, and substantiation.Yet,the employment of AI technologies by auditors in Iraq, and especially at University of Mosul, as well as their influence on audit evidence has been overlooked; thus, the collection of audit evidence is an important part in auditing process that guarantees accuracy and reliability of financial statements as well as compliance with regulatory standards. At the same time, though, traditional evidence-collection methods are increasingly ill-equipped for such tasks due to heightened complexity brought about by the fast pace of technological innovation in business processes and globalization—now combined with COVID-19 effects cascading through supply chains. These challenges are particularly relevant in a region such as the University of Mosul,Iraq where the auditing profession is still struggling to assimilate new technology and methodologies that can assist with leveraging audit evidence more effectively.

- Unique hurdles in adequately gathering audit evidence

i.Technological Integration and Expertise

The main challenge in audit evidence collection is the incorporation of modern technologies in the audit process. In common with their counterparts in other regions of the world, auditors in the University of Mosul, Iraq are challenged by having to adapt Artificial Intelligence (AI) and block chain into their practices. Technological expertise and the existing infrastructure in place may result in audit evidence not being collected adequately or analyzed properly(Ahmadu & Taimin, 2023; Al-Aroud, 2020; Al-Sayyed et al., 2021)

ii.Remote Auditing and the Accessibility of Data

The importance of remote audit capacity has been highlighted by the installment of the COVID-19 pandemic.Auditors have had to deal with the complexities involved in collecting evidence remotely, including how to ensure that they are collecting enough and relevant audit evidence while also catching possible fraud.(Grassa et al., 2022; Handoko et al., 2023; Ramadhan et al., 2022).The move away from traditional office-based working to remote and mixed-model services means we must learn new auditing methods that are effective outside of a central location.

iii. .Continuous Controls Monitoring (CCM)

CCM technologies are being used more, especially in the healthcare industry Due to the COVID pandemic. First, the adoption of CCM tends to be influenced by factors such as prior investments in technology and adequacy training/preparedness by audit department (Singh & Best, 2023).

iv.Machine Learning in Auditing:

1) Artificial intelligence (AI) and machine learning (ML) are being applied to auditing, for example in anomaly detection, risk assessment or predictive analytics. In this review, we combine the results of multiple studies to demonstrate various uses and advantages of ML in auditing.

v.Anomaly Detection

The purpose of anomaly detection in auditing is to identify patterns or deviations that are significantly different from the majority and obviously a potential outlier within financial data, which potentially denotes errors. Both supervised and unsupervised ML algorithms have demonstrated a lot of promise in this regards. For example, supervised techniques including deep learning and unsupervised methods like isolation forests and auto encoders have been used to detect anomalies in general ledger data overall replacing the manual checks involving random sampling that are subject to limitations. This enables them to effectively sample data so as to pick out journal entries that are at higher risk, greatly improving the credibility of financial audits(Bakumenko & Elragal, 2022).

vi.Risk Assessment

Embed RRN algorithms in your AI for several purposes but most satisfactorily to enhance the precision and efficiency of risk forecasting. Studies have adopted numerous ML models such as random forest, support vector machine (SVM) and AdaBoost to evaluate enterprise risk(Muslihatun et al., 2021).These models output risk indices by analyzing a large number of individual risk factors, thus providing auditors with valuable information on what potential risks a business might confront. Furthermore, AI techniques including machine learning have been proven to substantially reduce the work involved in risk assessment by identifying and predicting auditable high-risk areas (Muslihatun et al., 2021).

Research Objectives

1. The aim of the present study is to examine the effect of artificial intelligence AI technologies on audit evidence-gathering for auditors working in al-mosul university, as it based on this research question: The main objective of the study is:
2. Evaluate the Current Usage of AI Technologies in Audit: determining how much audit evidence collection processes at University of Mosul are currently using ai technologies.
3. Assess the Impact of AI Technology: Assessing the impact and influence of modern technologies, like an expert system or neural networks, on the effectiveness; efficiency; reliability for collecting audit evidence.
4. Identifying challenges and opportunities: Looking to identify the exact challenge of adopting AI technology by the auditors in collecting audit evidence, and what are potential opportunities due to new technologies for the collection of audit evidences.
5. To suggest strategies for a successful integration of AI technologies into the audit based on the study's results.

Research Questions

2) If we were to carry out the study, our research question will be in two:

1. How far are AI technologies currently used in the process of collecting evidence by auditors In University of Mosel?
2. What is the effect of AI technology on effectiveness and efficiency from the perspective of auditors at University of Mosul?
3. What are the challenges for University of Mosul auditors in adopting AI technologies to collect audit evidence, and how can these be mitigated?
4. What are the utilities of AI technologies in improving the process of gathering audit evidence? How might these utilities be employed by University of Mosul auditors?
5. What strategies would be suggested encourage the effective deployment of AI technology in the domain of auditing within University of Mosul?

Significance of the Study

1. This is the first study in Iraq, university of Mousl to estimate the prevalence of alleged medical malpractices during cataract surgery and their predictors. Hence, this study is important for:

2. Conclusion: Therefore, findings of this research would not only help to advance the audit practices by examining the influence of AI technologies on interview evidence-based auditing but also with regards to enthusiasm at the University of Mosul. It offers a view into how AI can increase audit efficiency and effectiveness.
3. Address Technological Integration Challenges. Tough the study tries to address the critical challenge of AI technologies' integration into audit practices, however, it aimed to provide recommendations and suggestions that may alleviate more smoothly adopt these new technologies.
4. Enhancing audit quality: This study will help in identifying the opportunities of using AI technologies for collecting audit evidence which can ultimately uplift the standards of audits leading to more reliability and credibility of financial reporting.
5. Policy/Educational Relevance: The results obtained could be valuable in suggesting implications for the adoption of audit and educational practices, as well as accounting/auditing education curricula, including AI-driven auditing.
6. Contribution to the Academic Literature: This study contributes and adds to the academic literature about the relation between AI technologies and auditing with a practical evidence on University of Mosul, also being used as frame reference for further researching in other contexts.
7. In conclusion, this exploratory study tries to investigate the transformatory power of AI technologies in audit evidence collecting dimensions. Accordingly, it gives important implications for auditors, policy makers and also operators in professional field along with researchers who are interested in auditing practice future evolution.

Beforehand, and depending on this literature review, the anticipative contribution to addition a project (**The extent of artificial intelligence technologies impact on audit evidence: An exploratory study on a sample of auditors at the University of Mosul**) about this topic field which includes auditing sciences & AI can be summarized as follows:

• Bridging the Research Gap

The research will also add to the scarce knowledge about the use and application of AI technologies in auditing profession, which is even less studied while speaking in Iraq and the University of Mosul. It is hoped that this region-specific focus can offer important perspectives regarding the manifest challenges and prospects of AI implementation in auditing within a distinctive cultural and regulatory atmosphere.

Empirical evidence based on auditors' perspective

An exploratory study employing a sample of the auditors at University of Mosul might contribute empirical evidence on how AI related technologies (expert systems and neural networks) are perceived to affect independent audit evidence capturing and analysis. This direct learning from auditors helps in designing and implementing AI solutions which are needed here catering to the unique challenges addressed by regional auditors on a day-to-day basis.

AI Technologies in Auditing

Description of AI technologies currently used in auditing

There has been a significant evolution in the field of audit with incorporation AI (Artificial Intelligence) technologies being increasingly becoming prevalent over traditional mechanisms. These tools include Robotic Process Automation (RPA), Machine Learning (ML), and Big Data Analytics(Seethamraju & Hecimovic, 2022).A milestone in this respect was the introduction of AI-based auditing techniques providing accurate and exhaustive audit functionalities(Hu et al., 2020).

According to Huang and Ozer (2020), the incorporation of AI technologies in auditing necessitates continuous audit capabilities, and hence, one may expect audit data analytics or machine learning as basic implants for such purposes. In addition, the AI audit tools being developed (such as those using Artificial Intelligence for evidence in natural language processing (NLP) methods), exemplifies the power of artificial intelligence to help with auditing processes and how it can be useful/faster/easier than current ways of conducting these audits through human effort.

IV. Impact of AI on Audit Evidence

Artificial intelligence (AI) is a highly technical science and an artificial field of studying that involves the creation or improvement of intelligent, when used in the ability to send arms on sentient beings would technically be considered tool-like. In short, it is nothing but a system which can utilize the human expertise in form of technology making work possible. By using AI technologies, the user can refurbish the traditional information transmission process with high doses of speed in their data transfer along with vastly diminishing costs for transference and essentially overcoming a significant number of bottlenecks related to quite a few problems(INTELLIGENCE, 2016).

According to a variety of accounting firms, AI use for auditing and advisory is saving time, improving speed in analyzing data, raising levels of accuracy or the depth and quality of business process insights provided as well generally enhancing client service. AI, a new influencing technology in the world that seeks to supplement human cognitive skills and judgment offers tremendous benefits to businesses adopted now (Munoko et al., 2020).

The audit profession will likely be transformed by the adoption of artificial intelligence (AI). Drawing on the technology–organisation–environment (TOE) framework, we provide a descriptive analysis of semi-structured interview data to explore which technological, organisational and environmental factors underpin AI tool adoption in audit practice(Seethamraju & Hecimovic, 2023).

In summary the interviews suggest that AI is regarded a "must-have" in the audits quality and efficiency. Areas with the largest total potential impact of AI include fraud prevention, risk assessment, anti-money laundering detection and bank secrecy act compliance, as well cybersecurity. Critical to this is that AI algorithms can process any data formats such an image recognition, parsing leases and contracts as well examining firms networks (e.g., supplier network or ownership structure) for potential laundering.(Fedyk et al., 2022).

The third axis-The practical side

1.**3 Research Community**: is a group of auditors from Internal Audit and Consulting, Universityof Mosul since its level on the impact of audit evidence by using artificial intelligence techniques to prepare him ready for it. In order to guarantee meeting the research requirements, the researcher tried as hard as possible to distribute (60) questionnaires on random pattern by hand over of large sample. Fifty recovered and all were eligible for statistical analysis: as demonstrated in Table (1)

Table 1: distribution of research questionnaires (60 in total were distributed, with the rest being collected for analysis because they are incomplete) This is equal to an 83% return.

Percentage	Number	Status
III. %100	**60**	**II.** NUMBER OF DISTRIBUTED QUESTIONNAIRES
%17	**10**	**IV.** NUMBER OF NON-RETURNED QUESTIONNAIRES
83%	**50**	**Number of returned questionnaires**

- Personal information (description of and diagnosis from the current research sample)

For the second component of our questionnaire, as a part that has been given out and few parts have come back (table2), we needed to characterize some key individual data about test studied in chosen field research.

Table (2): Descriptive Distribution of the Study Sample According to its Personal Information Field number Name Average number (%) 1 Auditor in University of Mosul -(Iraq-) Research sample according to personal variables Table (3) shows descriptive distribution according respondents` information for all auditors [N =50]. The table details about:

Education and Degree: Among members, 40% of them hold a master's degree, 40% have a doctorate, 6% are Certified Public Accountants (CPA), 4% hold an advanced degree, and 10% received Bachelor's degrees. Speciality: 24% with 5 or more years of experience, 30% with 6-10 years' experience, 20% with 11-15 years’ experience, 16% with 16-20 years of experience, 10% with more than 21 years in the field of their specialty.

Professional training courses for accountants: 30% of the members did not hold a certificate; 28% took 1 course; 20% took 2 courses and 22% took 3 or more training courses.

Number of professional training courses for auditors: 32% held no certificate at all; 26% had only one course; 22% took 2 courses and 20% took three or more such classes. Number of professional training courses for computer science and Internet technology: 30% took none at all; 36% took only one course; 26% took 2 courses and 8% took four courses.

Table 1: Summary of Education and Work Experience The summary table will give insight to your understanding about which the participants were concerning their educational background and work experience which is related to knowledge in accounting, auditogy and information technology.

Qualification	**Master's degree**	**Ph.D.**	**Certified Public Accountant (CPA)**	**Higher Diploma**	**Bachelor's degree**
N	**20**	**20**	**3**	**2**	**5**
%	**40%**	**40%**	**6%**	**4%**	**10%**
Specialization	**Less than 5 years**	**6-10**	**11-15**	**16-20**	**21 years or more**
N	**12**	**15**	**10**	**8**	**5**
%	**24%**	**30%**	**20%**	**16%**	**10%**

Number of training courses for the researcher in the field of accounting	**None**	**One course**	(i) Two courses	**Three courses or more**
n	**15**	**14**	**10**	**11**
%	**30%**	**28%**	**20%**	**22%**

Number of training courses for the researcher in the field of computers and the Internet	**None**	**One course**	**Two courses**	**Three courses or more**
N	**15**	**18**	**13**	**4**
%	**30%**	**36%**	**26%**	**8%**

Number of training courses for the researcher in the field of auditing	None	One course	Two courses	Three courses or more
N	16	13	11	10
%	32%	26%	22%	20%

Source: Prepared by the researcher (questionnaire results)

First: Description and Diagnosis of Study Variables

1. - Identification and diagnosis of the answers provided by respondents regarding how expert systems have influenced audit evidence.

This paragraph is the detail and diagnosis of expert systems in audit evidence dimension as a variable based on response states. Table 1 represents satisfied opinions between a sample of accountants and auditors on the influence of expert systems in audit evidence for assertions (X1 - X9), as general satisfaction proportion among respondents' replies with agreement responses (I strongly agree, I agree) was reached by mediatory to be equal to percentage value =57.78%). It can be observed from this that there is a moderate level of consensus in the answers given by the respondents about Influence on Audit Evidence, meaning that

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respondent opinions show an average tendency to positively influence Expert systems according to Likert scale) The mean disagreement for the auditors question is (16.22%), with a neutral answer of only(25.78%). Arithmetic Mean = 3.56, Standard deviation =1.09 Locally, the extent of mean agreement by respondents to items in impact of expert systems on audit evidence as measured obtained was (71.11%) which indicate that individual reflecting such paragraphs were rated medium - high according to their own perspective.

Table 3 shows that at the partial level, Notice. No. in para describes that expert systems work to solve problems automatically as they used many modern intelligent techniques to process a lot of data intelligently and submit reports very quickly. Therefore, it is more efficient with Arithmetic mean 3.70 and 1.07 of standard deviation and received relative importance of 74%. Whereas at the other end, Notice. No. in para exhibit the lowest level of relative importance of 68; Explain how expert systems contribute to the speed of planning, evidence gathering, and audit program steps and how they reduce costs and try to complete work in the least possible time with Arithmetic mean 3.40 and 0.99 of standard deviation.

Table (3) Frequency distributions, arithmetic means, standard deviations, and relative importance of the expert systems variable and their effect on audit evidence

Items	Response Scale	Arithmetic Mean	Relative Importance %	Standard Deviation	Item Rank
Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)	
%	Count	%	Count	%	Count
X1	71.6	0.84	3.58	0	0
X2	68	0.99	3.4	4	2
X3	72.8	1.16	3.64	2	1
X4	68	1.24	3.4	6	3
X5	68.8	1.09	3.44	2	1
X6	73.2	1.16	3.66	0	0
X7	70.8	1.12	3.54	4	2
X8	72.8	1.16	3.64	2	1
X9	74	1.07	3.7	2	1
Overall Average	17.11	40.67	25.78	13.78	2.44

<u>Source</u>: Prepared by the researcher based on the outputs of the program (SPSS V.26) n=50

-2Description and diagnosis of respondents' answers about the impact of data mining techniques on audit evidence.

This paragraph refers to the description and diagnosis of the variable of the impact of data mining techniques on audit evidence in light of the respondents' answers.

The data in Table (2) shows an agreement between the opinions of a sample of accountants and auditors regarding the impact of data mining techniques on audit evidence for statements (Y1-Y9), as the general agreement rate for the respondents' answers with agreement (I totally agree, I agree) reached (51.11%). This indicates that there is a relative degree of agreement in the respondents' answers on the impact of data mining techniques on audit evidence, meaning that the opinions of the respondents tend towards relative positivity based on the five-point Likert scale. The general disagreement rate for the respondents' answers on the impact of data mining techniques on audit evidence was (16.89%), while the percentage of neutral answers was (30.44%). The arithmetic mean was (3.45) and the standard deviation was (1.09). The relative importance rate of the variable of the impact of data mining techniques on audit evidence reached (68.93%), which means that the respondents agreed to a (medium to good) degree on these paragraphs according to their personal point of view.

At the partial level, paragraph (Y1) which indicate artificial intelligence can be employed to transform the document examination process in various strategies such as data mining with a highest relative importance of 74%, average is equal (3.70), and standard deviation value equals to(0.84); while on lowest area reached by vehicle recognition was obtained for Paragraph(Y7) through process mining an auditor enables detailed evaluation per numerous transaction types enlisted under processing variables containing wide range classes however it recorded a lower mean comparing with other areas equaling 63:60 %;(mean=3.18),(SD =1/12).

Paragraphs	**Measurement Scale**	**Mean**	**Relative Importance%**	**Standard Deviation**	**Rank of Paragraphs**
	I strongly agree (5)	**Agree (4)**	**Neutral (3)**	**Disagree (2)**	**I strongly disagree (1)**
	%	**Number**	**%**	**Number**	**%**
1	**74**	**0.84**	**3.7**	**0**	**0**
2	**71.2**	**0.99**	**3.56**	**0**	**0**
7	**68**	**1.16**	**3.4**	**2**	**1**
6	**68**	**1.24**	**3.4**	**4**	**2**
3	**69.6**	**1.09**	**3.48**	**4**	**2**
Y6	**4**	**69.6**	**1.16**	**3.48**	**4**
Y7	**9**	**63.6**	**1.12**	**3.18**	**6**
Y8	**5**	**68.8**	**1.16**	**3.44**	**4**
Y9	**8**	**67.6**	**1.07**	**3.38**	**6**
Overall Average	**13.44**	**37.67**	**30.44**	**13.56**	**3.33**
Total	**51.11**	**30.44**	**16.89**		

Source: Prepared by the researcher based on the outputs of the program (SPSS V.26) (n=50)

The frequency distributions, means and standard deviations of the mining technology variable and its effect on audit evidence are shown in Table (4).

The fact that this paragraph discussed details on data mining technology use as an audit evidence variable and the diagnosis in line with what is expressed by the paragraphs above it except due to answers from respondents.

From Table (3), it is clear that there is concordance in opinions of a sample of accountants and auditors about items related to using data mining technology in audit evidence paragraphs wise for the phrases denoted by Z1-Z7, where general agreement percentage amounted

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66.29%. Therefore, the respondents' opinions are more biased toward agreement on using data mining technology in audit evidence paragraphs with general disagreement rate of 20.57% (based off from Likert five-level scale). With a rate of 13.14% neutrals, the average was 3.72 and standard deviation was (1.22), The degree of importance to use data mining technology in audit evidence came by approximately about(74-46%) which all paragraph found according to personal point viewed medium -good agreements from are respondents
At the partial level, paragraph achieved the highest relative importance which is 79.20%, Paragraph represents the contribution of the use of data mining applications in dealing with large groups of complex data that are unable to deal with manually. With arithmetic mean and standard deviation 3.96 and 1.16 respectively, while Paragraph obtained the lowest relative importance good 71.20%, which represents the contribution of the use of data mining applications in adapting the collection of audit evidence and its sufficiency. The arithmetic mean and standard deviation are 3.56 and 1.18 respectively.

Table 5 - Frequency Distributions, Arithmetic Means and Standard Deviations Relative Importance of the Artificial Intelligence Variable in Audit Evidence:

	Strongly Agree (5)	Agree (4)	Neutral (3)	Disagree (2)	Strongly Disagree (1)
6	72.8	1.27	3.64	6	3
2	75.6	1.26	3.78	4	2
7	71.2	1.18	3.56	6	3
1	79.2	1.16	3.96	2	1
5	74	1.11	3.7	4	2
3	74.4	1.23	3.72	4	2
4	74	1.29	3.7	2	1
Overall Average	30.57	35.71	13.14	16.57	4
Total	66.29	13.14	20.57		

Source: Prepared by the researcher based on the outputs of the program (SPSS V.26) (n=50)

T. Summary of the description of the study variables:

Upon what has been previously presented, it could be stated that all responses of all variables were above the supposed arithmetic mean due to 3. Table 4 shows the relative importance of the study variables to a sample of accountants and auditors at the University of Mosul from their point of view through the value of the arithmetic mean and the standard deviation and relative importance, which shows us that the most important variable is the artificial intelligence variable. As the value of the arithmetic mean of 3.72 and the standard deviation 1.22, with a relative importance of 74.46%. On the other hand, comes in the second place the expert systems variable, as the value of the arithmetic mean was 3.56, and the standard deviation was 1.09, with relative importance of 71.11%, while the data mining technology variable show us as the least important variable, as the obtained value of the arithmetic mean was 3.45 with a standard deviation of 1.09, and a relative importance of 68.93%.

V. TABLE (6) THE RELATIVE IMPORTANCE OF THE STUDY VARIABLES

T	Variables	Arithmetic Mean	Standard Deviation	Relative Importance %	Rank
1	Expert Systems	3.56	1.09	71.11	2
2	Data Mining Technology	3.45	1.09	68.93	3
3	Artificial Intelligence	3.72	1.22	74.46	1

Source: Constructed by the researcher according to the SPSS V.26 program outputs (N = 50(

Step 2: Testing Reliability of the Tool (Relibility Test for Questionnaire)

To assess the reliability of the instrument, Cronbach's alpha coefficient was used by (Feldt 1989, Brennan) & who classified stability coefficient values into two levels that at more than (70%) are considered high level and otherwise is low value for an stability coefficient if it were less than (70%), Table.(6).Results can show that in table six shows that according to every attribute the results indicated satisfactory amount of internal consistency as well figurate alphas among all variables resulting stratified maximum item scores(Coeficient>0.92).This indicates highly stable questionnaire indeed.

For the assessment of reliability of scale Feldt 1989, Brennan has used Cronbach's Alpha Reliability Coefficient and then divided it into two levels with value equal or exceeding (70%) for satisfactory [21], while less than that is unsatisfactory Table-6 shows values closer to Stratify-Cronbach-scale supported by total variation; results convey valid constructs amongst scales measure different dimensions but were found strong due to their compatibility on one confirmatory dimension.

$$\alpha_{st.} = 1 - \left[\frac{\sum_{i=1}^{m} \sigma_i^2 (1-\alpha_i)}{\sigma_c^2}\right]$$

Reliability Test

Cronbach's alpha was employed to assess the internal consistency of each variable (expert systems, data mining and artificial intelligence). Results are given in Table 7. Reliability Test

Variable	**Cronbach's Alpha (Individual)**	**Cronbach's Alpha (Combined)**
Expert Systems	0.94	
Data Mining	0.92	
Artificial Intelligence	0.82	0.95

Source: Researcher's calculations based on SPSS v.26 output (n=50)

Source: Feldt, L. S., & Brennan, R. L. (1989). Reliability. In R. L. Linn (Ed.), Educational measurement (pp. 105-146). Macmillan Publishing Co., Inc; American Council on Education.

(1) Hypothesis Testing

In this experiment, the Wilcoxon Signed-Rank Test was used to verify whether each of the (expert systems, data mining and artificial intelligence) has influenced on evaluation guide. Null-hypothesis (H0): There is no effect Alternative hypothesis (H1): An effect exists ,The results in Table 8 and Fig .1

1. Expert Systems: The evaluation guide was significantly affected by expert systems (p < 0.05). The average rank). 67; indicating that it ranks on more than intended or expected. As a result, the null hypothesis is no longer supported and we are accepting the alternative pushed forward.
2. Data Mining: Data mining had a significant effect on the evaluation guide (P < 0.05). The observed mean rank 3.50> expected MR (0,Fetches) = 3 ConclusionH0 Null hypothesis is rejected and Ha Alternative Hypothesis would be accepted
3. Artificial Intelligence: A Fine-Grained Evaluation Guide-Correlations between Code and Human Assessments p < 0.05 The mean rank observed (3.57) is higher than the expected one(3). This result will tell us the reject and accept status of Null hypothesis, because for null acceptance we need P >= alpha and if it is less then receptor rejected hence alternative accepted.

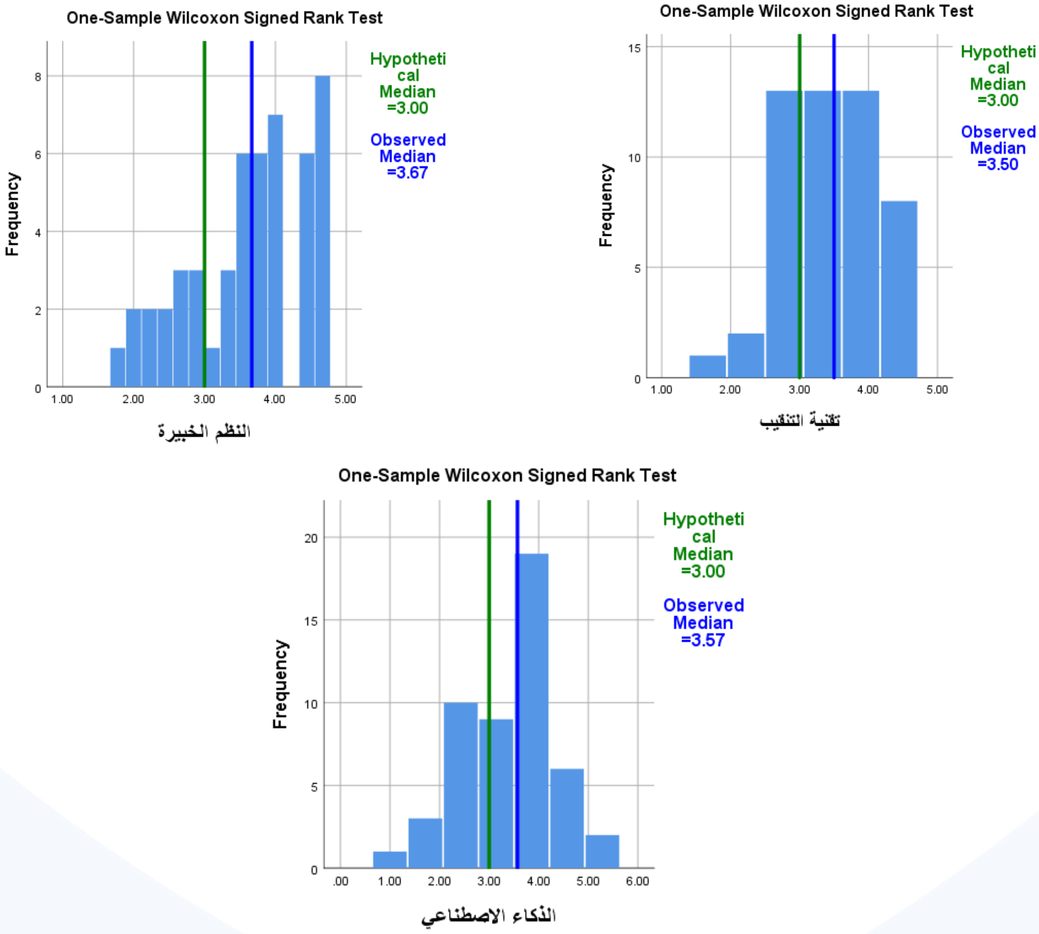

Fig 1 Hypothetical and observed median values of the study variables Source: Researcher own calculations using SPSS v.26 output (n=50)

Axis IV: Conclusions and Recommendations

4.1 Conclusions

1. There is no doubt that AI technologies have revolutionized several practices within accounting and has played a huge part in the future of auditing, skills and other functions.
2. AI assists in improving audit evidence by providing the auditors and accountants with a massive database of information as well data which can be scrutinized to get more audit evidences.
3. AI enables the different aspects of specialization and applications that have multiple functions: hence integrates these functionalities in improving what auditors do, thereby making them better at their job.
4. The use of artificial intelligence technologies reduces potential costs for the implementation at large enterprises because programming solutions does not require scientific work and practical knowledge as it should be with auditors, but general programs can do a lot to solve some tasks in the audit process.

Conclusion

Summary of Findings

The aforementioned insights and findings drawn from the study "The **extent of artificial intelligence technologies impact on audit evidence/An exploratory study on a sample of auditors at University of Mosul**" can be substantially important considering that they reveal the actual level of development and implementation as well as its further potential to help auditing practice. In summary, the key findings of this research study include:

1. The auditors have been in a continuous attempt to adopt more AI technologieswhere significant part of the sample has indicated that they use AI tools within their auditing practice at the University of Mosul.
2. AI was considered to affect the audit evidence greatly. There were views from auditors experiencing increased efficiency, accuracy and completeness of obtaining and analyzing evidence as a result of using AI.
3. Auditors understand that AI can improve the quality of audit evidence through expanded data analytics, pattern and outlier detection, as well as lower risk of human mistake.
4. The paper's findings have some important implications for the future of AI adoption, including overcoming barriers to entry with little or no relevant skills and training, managing potential over-reliance on capability claims made by tech companies.
5. Our results imply that successful employment of AI in the auditing industry is an endeavour, done optimally if it combines human expertise capability with the one provided by AI.
6. The results speak to the degree of AI adoption by auditors at University of Mosul, which is helping them enhance efficiency and precision in acquiring audit evidence completely. Auditors have also accepted that AI can improve audit quality by enabling more data analytics, spotting patterns and outliers in huge datasets more efficiently than a human being could. Nonetheless, there are challenges in terms of training the models and mitigating risks associated with AI-based centralization. To audit, AI needs the human touch or should it be to successfully undertake an audit.

7. The results from the study illustrate necessary avenues for further research to investigate not only AI and its impact on audit evidence quality, but also ethical considerations related to adopting AI in auditing over a long term. The study indicates reconciling human intelligence with artificial thinking is non-negotiable when it comes to effectively applying AI in audit. This underscores the relative importance of ongoing auditor education and training in order to work with AI tools intelligently while maintaining professional skepticism and judgement.

Recommendations

1. That necessitates the need of writing in maneuvers, encoding them with software and treasure on databases of methodologies for auditing evidence procurement.
2. Auditors who have a full suite DAAS tool chain has to be known with all the electronic operating system and application so that these experts can carried their responsibilities effectively, which then support field work not only by simply covering them cloud based program for more information/data collection.
3. Training courses - need for the enhancement of professional performance ability among auditors, to tap AI techniques in the areas so planning; evidence collection and report preparation.
4. Generalization of intelligent software for building collecting and converting audit evidence processing in computer assess enables to deform a new facelift in the quality ensuring level during conduction of auditing work.
5. Moreover, the training auditor question also emerges with the pace of technology developing at a rapid speed & possible applications for artificial intelligence in obtaining audit evidence.
6. The following suggestions are proposed as a way to address these weaknesses and improve future research:
7. Think About Effect Sizes: In line with p-values, researchers ought to report effect sizes in an effort to determine the sensible significance of their findings. Likewise, we argue that effect sizes lead to a richer understanding of the size of AI's impact on audit evidence
8. Use Robust Statistical Methods: In such studies it is appropriate to use statistical methods that are robust against violation of normality assumptions (e.g. non-parametric tests, bootstrapping).
9. Triangulation with Qualitative Data: Creating a fuller understanding of how AI influences audit evidence can be achieved by combining hypothesis testing and qualitative data from interviews or focus groups. While it will give us a realization of the statistical findings, qualitative data may explain why these happen and can provide some insights with regards to practical implications.

Concluding Remarks

1. Governments, organisations and academia will have a better understanding of the impact of Artificial Intelligence (AI) technologies on the auditing profession through this work. This in turn can contribute to existing research into AI’s effect on professional judgement.

2. This paper contributes to the existing literature and practice by presenting empirical evidence from auditors as a sample at University of Mosul regarding their adoption level AI technologies and how they could affect audit evidence.
3. The results highlight the significant role that AI can play in improving audit quality and efficiency; however, they also point out some challenges and issues relevant for future investigation. audit continues to grow in prevalence, it is important that the profession not only adapts and learns how to capitalize on AI's benefits but also develops the skills and frameworks needed to do so while managing its risks
4. This article provides a platform for future research to delve deeper into the implications of AI on audit evidence within various settings, and studies focusing on individual technologies as well as their specific uses in practice. Future research may develop guidelines for deploying AI in auditing responsibly and effectively
5. Given that the auditing profession is playing catchup with respect to AI, these are crucial findings that will influence practice and thus also education/training while helping guide current regulatory initiatives. Embracing the opportunities and meeting the challenges of AI will allow for further transformation of today's auditing profession, ensuring that it can continue to adapt to meet its objective of providing high-quality assurance services in a business environment driven by increasingly complex and fast-moving data.

2) Scales will be taking in Questionnaire and references:
(Baldwin et al., 2006; Dai & Vasarhelyi, 2016; Greenman, 2017; Issa et al., 2016; Kokina & Davenport, 2017; Louwers et al., 2018; Moffitt et al., 2018; Omoteso, 2012; Raphael, 2017; Sutton et al., 2016; Yoon et al., 2015)

3) Questionnaire: The Impact of Artificial Intelligence Technologies on Audit Evidence

Scale:

1Strongly Disagree, 2Disagree, 3Neutral, 4Agree, 5Strongly Agree

1. Scientific evidence exists of artificial intelligence (AI) technologies that could reduce the time required for audits.
2. Augmented audit evidence — AI can increase the accuracy and completeness of existing audit evidence, without increasing auditor workload.
3. AI in auditing can lower the risks of errors.
4. These deep-learning-enabled tools are also able to help uncover potential fraud.
5. Evaluating large volumes of data is something AI can assist with, and it allows auditors to focus on these as higher-risk areas.
6. This new wave in auditing involves large investments in technology and training alongside AI.
7. AI could present issues as to the auditor's professional judgement and scepticism.
8. AI use in audits may provoke data privacy and security concerns.
9. To use AI effectively, auditors need to gain new skills that exist at the collaborative intersection of emerging technology and specialized knowledge.
10. Run the world to audit will change auditing standards and regulations Golden legacies survive.

11. Many of the same AI technologies, from machine learning to data mining, that have helped auditors identify patterns and anomalies in large datasets can be harnessed by privacy professionals.
12. Techniques from Natural Language Processing (NLP) can help auditors to analyze unstructured data like contracts and e-mails and extract audit-relevant evidence.
13. The efficiency of the audit process is also improved by AI-powered tools automatizing repetitive tasks and thus freeing the auditors to concentrate on more important higher-risk areas where value-added professional judgment is necessary against conventional or usual ISQM 1.
14. Integration of AI technologies with auditing may result in substantial infrastructure needs, software costs and staff training
15. These AI-based systems can improve the accuracy and completeness of audit documentation, thereby reducing exposure to errors and omissions.
16. However, some issues with ethical implications arise when considering using AI in auditing: for example the possible bias of algorithms or the necessity other transparency in decision-making.
17. In leveraging AI technologies in their work, auditors will require new skills and knowledge including data analytics and AI literacy.
18. Changes to auditing standards and regulations could be necessary to account for the challenges (and benefits) of using AI in audits.
19. AI-enabled tools can improve the efficacy of fraud detection by pinpointing out-of-the-norm patterns and transactions that could be an indicator of an illicit practice.
20. Effective usage of AI in auditing will necessitate cooperation among auditors, IT workers and data scientists to develop, test, and implement the system.

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