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How external auditors in the Arab Republic of Egypt perceive and accept machine learning technologies in their auditing?

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Abstract

Our study aimed to investigate the perspectives of external auditors on the advantages and ease of use of machine learning in ARE auditing. Through analysis, the differences between local and international audit offices in the ARE regarding the ease of handling machine learning are revealed. The study gathered information from one hundred external auditors who work for both local and international audit offices in the ARE. The questionnaire was distributed using both an online survey tool and through manual distribution during in-person interviews. The study's findings suggest that external auditors have shown limited interest in and perception of the ease of use of machine learning, and they do not have differing opinions regarding the ease of using machine learning in auditing. The main reason for the importance of the research's findings is the absence of study evidence on machine learning's apparent advantages and simplicity of usage in external audits within the ARE. Thus, this research provides new empirical information by evaluating the assessments of external auditors about the handling of machine learning in the ARE. This paper fulfills an identified need to study whether the Arabic Republic of Egypt's (ARE) external auditors confirm the benefits and usability of machine learning (ML).

Keywords: Advantages, Auditing, External auditors, Handling, Machine learning.

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1. Introduction

Recognizing the many advantages offered by advanced technology, it is important to acknowledge its associated risks. Advanced technology improves accounting performance, enhances communication, boosts employee retention, increases revenue, and raises client satisfaction [1]. However, it also introduces risks such as fraud, data security issues, and potential job loss.

As the business environment becomes more complex, leveraging technology-based decision aids is increasingly crucial. Artificial intelligence (AI), as defined by the OECD [2], is transformative, capable of making predictions, suggestions, or judgments to achieve human-specified objectives. For external auditors, AI, alongside data analytics, machine learning (ML), and blockchain, significantly impacts their work [3]. These technologies drive innovation in auditing, necessitating auditors to master these tools to maintain assurance standards [4]. stress the importance of using advanced technologies in audit tasks to ensure effective assurance on complex systems. AI integration is vital for enhancing the accuracy and efficiency of accounting processes [5].

Audit firms have heavily invested in new technologies to enhance audit quality and effectiveness, despite challenges such as data security, implementation costs, skill shortages, and potential overreliance on technology [6]. ML, a subset of AI, automates analytical model creation, increasing operational efficiency. ML techniques analyze data, detect patterns, and predict outcomes, continuously improving through iterative processes [7]. ML includes supervised learning, which uses labeled data; unsupervised learning, which identifies patterns without labels; and reinforcement learning, which maximizes cumulative rewards by guiding agent actions [8]. ML's potential to enhance audits is recognized, though there is a misconception that it will replace human auditors [9].

Technology allows auditors to analyze entire datasets, focus on anomalies, and have insightful discussions, improving audit quality. This study explores external auditors' perceptions of ML's usability and utility, comparing local and international auditors' views. Previous studies, including those by Ucoglu [10], Barrak [11], and Machine [12], reveal auditors' readiness to adopt ML technologies. The Big Four firms have developed various ML tools to automate and manage the audit process effectively.

ML enhances audit speed and quality, as demonstrated by Deloitte's Argus, which identifies patterns and outliers in contracts [13]. However, emerging technologies pose risks such as data security, implementation costs, skill shortages, and disruptions to traditional auditing [6].

In the context of Egypt, the country has made significant AI advancements. Egypt's Ministry of Communications and Information Technology (MCIT) has partnered with international firms to implement AI projects and build capacity in AI [14]. Egypt's national AI strategy focuses on education, practical data usage, and private sector data release (MCIT, 2021This study's findings on external auditors' knowledge and perceptions of ML can provide valuable insights for regulatory authorities and offer guidance for future research. Findings on external auditors' knowledge and perceptions of ML can provide valuable insights for regulatory authorities and offer guidance for future research.

We structure the paper as follows: Section 2 examines the pertinent literature and formulates research hypotheses, Section 3 covers research design and sample selection, and Section 4 discusses the findings.

2. Review of the Literature and Formulation of Hypotheses

2.1. Conceptual Structure

The Technology Acceptance Model (TAM), introduced by Davis [15] in Figure 1, [9], is a well-established paradigm that explains the elements that influence humans' acceptance and utilization of technology. It is highly helpful in comprehending the adoption of technology by specifically examining two crucial variables: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). In this study, we examine the acceptance of machine learning (ML) in auditing quality among external auditors in the Arab Republic of Egypt (ARE). Specifically, PEOU and PU serve as independent variables affecting the auditors' propensity to adopt ML technologies.

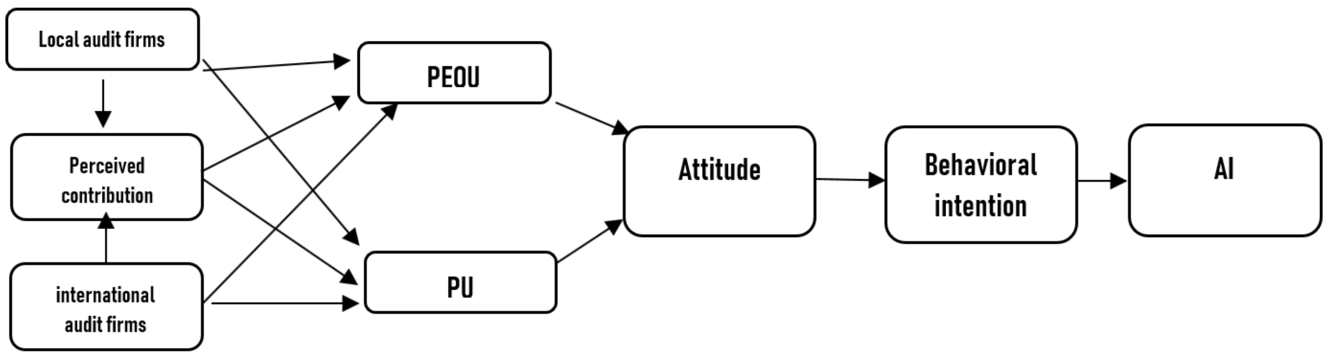

Figure 1.
Technology Acceptance Model-Adapted Research Framework [9] with modifications.

2.1.1. Technology for ML

Machine learning (ML) lies at the intersection of computer science and artificial intelligence (AI), leveraging data and algorithms to enable computers to learn patterns and make decisions without explicit programming. Its applications are extensive, spanning industries such as finance, healthcare, and education, driving innovation and efficiency [9].

AI has been utilized in the auditing profession to improve many parts of the auditing process, such as detecting errors, identifying anomalies, preventing fraud, and creating prediction models. AI-powered systems can quickly and accurately analyze vast amounts of data, improving audit efficiency and effectiveness [16]. The ability of AI to automate high-level duties can also lead to increased productivity and the emergence of new roles within the auditing profession [17].

The evolving landscape of technology, particularly AI, is reshaping the roles and responsibilities of accountants. AI allows accountants to transition from routine tasks such as bookkeeping to more strategic functions like advisory services and growth planning, leveraging their expertise to provide valuable insights [18]. Supervised learning, a key technique in ML, involves training on labeled datasets to make accurate predictions, aiding in tasks like auditing judgments [19, 20]. AI in accounting software improves risk management, invoice processing, and customer service while reducing labor costs [21].

Despite its potential, there are common misconceptions about ML. For instance, reinforcement learning is distinct from supervised and unsupervised learning, and biases such as selection, learning, and modeling bias can occur in any ML algorithm [13, 22-24].

2.1.2. ML's Use in Audit

ML holds significant promises in improving data analysis for auditors and accountants, streamlining processes, reducing errors, and enhancing overall efficiency [10]. ML algorithms can automate tasks like risk assessment, accounts payable and receivable management, and cost reporting. Leading accounting firms, including the Big Four, have invested heavily in AI and ML to develop platforms and solutions that integrate these technologies, highlighting their potential to revolutionize auditing practices [25, 26].

ML methodologies also enhance the accuracy of going concern evaluations, reducing judgment errors, and addressing limitations of traditional statistical models [3]. The transformative impact of ML and AI in auditing underscores the importance of preparing future auditors to effectively utilize these technologies [27].

2.2. Development of Research Hypotheses

Based on the literature, we propose the following hypotheses:

$H_{1:}$ The use of machine learning in auditing is accepted by both local and international audit offices in the ARE.

Deep reinforcement learning (DRL) algorithms have been effective in handling complex control tasks, but they face challenges such as noisy exploration strategies and sensitivity to hyperparameter selection. Collaborative Evolutionary Reinforcement Learning (CERL) is one approach to address these challenges, enhancing sample efficiency and policy optimization [28]. ML techniques, including speech recognition and autoencoders, offer valuable capabilities for fraud detection and anomaly identification, though interpretability remains a critical issue [29, 30].

$H_{2:}$ Both local and international audit offices in the ARE find machine learning remarkably helpful in auditing.

Digital transformation is increasing data volumes and challenging traditional sampling methods, necessitating advanced ML techniques to mitigate sampling [31, 32]. Current sampling approaches in auditing are becoming obsolete due to the growing volume of data, requiring more comprehensive audit techniques leveraging data analytics [33, 34].

$H_{3:}$ International and local audit offices in the ARE experience different levels of ease when adopting machine learning.

Unsupervised learning techniques are essential for detecting anomalies and patterns in data, complementing supervised learning in fraud detection and pattern recognition [35, 36]. These techniques allow auditors to detect fraud attempts, accidental mistakes, and unexpected entries, enhancing the thoroughness of audits [37-42]. Implementing anomaly detection techniques allows auditors to devote more time to investigating anomalies, reinforcing their importance in identifying risks within financial processes [43].

H4: Both international and local audit offices in the ARE have significantly different opinions about the effectiveness of machine learning.

3. Design of Research

3.1. Methodology of Research

A team of three auditors and five academics from the Accounting Department at Al-Azhar University's Faculty of Commerce in Egypt assessed the poll to confirm its authenticity. In order to collect pertinent data, a total of 100 external auditors in the ARE were selected as participants. The questionnaires underwent initial pilot testing by three external auditors and were subsequently excluded from the data analysis. Minor phrasing changes were made based on their feedback.

The initial part of the questionnaire captures the respondents' level of expertise, years of experience, and other qualitative characteristics. All respondents held positions such as audit managers, audit partners, and senior auditors. Six elements were used to gauge the perceived ease of use of machine learning, and six more elements were designed to measure its perceived usefulness. The primary methodology employed in this study is quantitative, utilizing a Likert scale questionnaire (5 = Strongly Agree to 1 = Strongly Disagree). The questionnaire was distributed manually during in-person interviews and via Microsoft Forms. Initially, demographic characteristics were examined, and the second section assessed the opinions of domestic and international audit offices regarding the usability of machine learning. Simple questions were used to avoid confusion, and this approach was selected for its ease of use.

3.2. Study Specimen

The study population consisted of 120 external auditors from both types of audit offices in the ARE. The questionnaire addressed the following demographics of external auditors:

Gender
Qualification categories
Experience
Position
Classification of audit offices
Professional certifications

The questionnaire was distributed manually during in-person interviews and via an online survey platform. As a result, 100 complete questionnaires were received and utilized for the study. Of these, 40% of the participants were affiliated with global audit companies, while 60% were from local audit offices. The first question revealed that 30% of the respondents were female, whereas 70% were male. The majority of respondents (50%) possessed a bachelor's degree, while 35% held a master's degree and 5% earned a Ph.D. In addition, 10% of participants possessed supplementary qualifications. In terms of years of experience, most respondents (70%) had over 15 years of auditing experience. A small percentage (8%) had between zero and five years of experience, while 13% had between six and ten years of experience. Another 9% had between eleven and fifteen years of experience.

Regarding the fourth question, 41% of the respondents held managerial positions, 27% were senior auditors, 11% were audit partners, 3% were accountants, and 18% had different roles in their professional careers. In addition, 1% of the participants possessed CIA certifications, 2% possessed ACCA certificates, and 2% had CPA credentials. The survey states that 38% of external auditors have local qualifications, while 57% of participants hold other professional certificates.

3.3. Data Gathering Technique

An online survey was created and participants were provided with access to it through a link and also through manual distribution during face-to-face interviews. The participants consisted of audit partners, managers, seniors, or staff members who were authorized in this field from both types of offices functioning in the ARE. Participants were requested to express their level of agreement with statements by selecting from alternatives such as agree, strongly agree, disagree, strongly disagree, or no opinion. The variables listed in Table 1 were employed to assess the perceived utility and simplicity of employing machine learning. The survey's inquiries were adapted from Noordin and Albawwat and Frijat [44].

A study was undertaken to analyze the perception of external auditors towards machine learning, using the technology acceptance model. The focus of the study was on ARE external auditors.

Table 1.
Elements for expected benefit and Ease of use of ML.

PEOU of Machine Learning (EBEU/QOIS/TSSQ Tables 1,2,3**)**	
Code	Elements for EBEU of (ML).
EBEU 1	The use of ML increases auditing process performance.
EBEU 2	The use of ML increases auditing process efficiency.
EBEU 3	I find ML service useful during my examination and auditing.
EBEU 4	I notice an increase in the collection of evidence when using ML.
EBEU 5	I notice a decrease in time spent when using ML.
EBEU 6	I would have no trouble picking up the ML systems and tools needed for audits.
EBEU 7	I find it easy to be skilled in the use of ML.
EBEU 8	Training had a positive impact on ML.
EBEU 9	I find pleasure in dealing with ML.
EBEU 10	I can control all the elements in an easy and clear way.
EBEU 11	Getting ML systems and tools to accomplish what I want in auditing is something I find easy.
EBEU 12	I find pleasure in dealing with ML.
EBEU 13	I can control all the elements in an easy and clear way.
EBEU 14	I will communicate in a clear and understandable manner when using ML systems and tools for audits.
EBEU 15	I find it flexible to work with ML systems and tools in auditing.

Table 2.
Elements for the Quality of information and service of ML.

Code	Elements for QOIS of (ML)
QOIS 1	ML provides information relevant to my job.
QOIS 2	ML system gives easy-to-understand information.
QOIS 3	The information output from ML is straightforward.
QOIS 4	ML system enables me to provide information in an appropriate format, especially when writing a report.
QOIS 5	The information content that can be provided in ML is very good.
QOIS6	The information provided through ML system can be updated to keep pace with the times, achieving the objectives of auditing process.
QOIS7	I consider the integration of the information that can be provided through ML system sufficient for the purposes of auditing and examination.
QOIS8	The reliability of the information via ML system is considered high.
QOIS9	I can get the information from ML system at the time I want.
QOIS10	ML system has a modern interactive interface.
QOIS11	ML system has an attractive user interface.
QOIS12	ML system provides the perfect solution for what I ask.
QOIS13	ML system provides fast service for what I ask for.
QOIS14	ML gives me individual attention and takes into account my specific needs.

Table 3.
Elements for Technical support & System quality of ML.

Code	Elements for TSSQ of (ML)
TSSQ 1	ML program provides a clear explanation of the tasks and the elements in it.
TSSQ 2	I do not find clear solutions to all the problems that I encounter in the explanation integrated with the program.
TSSQ 3	I can easily explain ML.
TSSQ 4	I can solve the problems that I face through the explanation provided by ML integrated with the program.
TSSQ 5	The number of steps required to complete one task in ML system is small.
TSSQ 6	The steps involved in completing a specific task in ML system follow a logical sequence.
TSSQ 7	Executing a process in ML system always leads to an expected result.
TSSQ 8	Organizing information on the screens of ML system is easy and clear.
TSSQ 9	ML system has easy, natural and predictable screen changes.
TSSQ 10	ML system responds quickly during the stressful hours of daily work.

Table 4.
Elements for Trust & Benefits of use of ML.

Elements for PU of Machine Learning (TBOU/SU Tables 4,5)	
Code	Elements for TBOU of (ML).
TBOU 1	My experience with ML system is better than I expected.
TBOU 2	I feel that the use of ML system is important to increase the effectiveness of auditing process.
TBOU 3	The day will come when ML will replace traditional learning.
TBOU 4	The ML system is offering a higher quality of service than I had anticipated.
TBOU 5	I made sure that most of my expectations were met using ML system.
TBOU 6	I'll be able to do work faster in my future auditing career because to the use of ML systems and tools.
TBOU 7	ML technologies and systems will help me perform better as an auditor going forward.
TBOU 8	My productivity will enhance in my future auditing work when I employ ML systems and tools.
TBOU 9	My efficacy in audit job would increase with the usage of ML systems and tools.
TBOU 10	It will be simpler for me to perform my future auditing work if I use ML systems and tools.
TBOU 11	I think ML tools and systems will be helpful for my future auditing work.

Table 5.
Elements for Satisfaction and Usability of ML.

Code	Elements for SU of (ML)
SU 1	Satisfied with the performance of ML system service.
SU 2	I am pleased with my experience using ML system.
SU 3	My decision to use ML system was wise.
SU 4	I use ML system often.
SU 5	I will use ML system on a regular basis in the future.
SU 6	I would highly recommend ML system to others.

4. Data Interpretation and Conclusions

4.1. The Instrument's Validity and Reliability Tests

Using the unidimensional reliability test, we look at the Cronbach's Alpha value to confirm the validity of the survey elements. There were forty-five (54) survey elements that were tested: 17 elements for PU of machine learning (11 from TBOU and 6 from SU) and 39 elements for PEOU of machine learning (15 from EBEU/14 from QOIS/10 from TSSQ). Given that Cronbach's Alpha is at the proficient level, the reliability test result for the survey elements was 0.972, as shown in Table 6.

Table 6.
Validity and reliability test.

Cronbach's Alpha	Number of Elements
0.972	54

4.2. Evaluation 1: A Detailed Examination of PEOU

Descriptive statistics provide percentages and frequencies for two different types of data: ordinal and nominal. Furthermore, when it comes to continuous data, descriptive statistics encompass various measures such as averages (mean, median), ranges, and standard deviations. Frequency refers to the number of participants who can be classified as belonging to the same group or category. Understanding the distribution of the sample across different groups and categories can be quite beneficial. The percentage has been computed to determine the portion of the sample that matches the specified frequency. The mean is typically the calculated average. The mean represents the average unit for an element. The spread of those units in relation to the mean is described by the standard deviation.

Table 7.
Perceived utility and simplicity of use Characteristic Statistics.

	PEOU		PU	
	(1) Local Audit offices	(2) Int. Audit offices	(1) Local Audit offices	(2) Int. Audit offices
Valid	60	40	60	40
Mean	3.998	3.827	3.966	3.783
Std. Deviation	0.285	0.227	0.316	0.430

The respondents from whom the data were collected were two groups of audit offices in the ARE: Local Audit Offices (n = 60) and International Audit Offices (n = 40). Additionally, Table 7's descriptive statistics, which address Hypotheses H1 and H2, demonstrate how local audit offices rate the overall usability of machine learning, with a mean score of 3.998 (SD=0.285). The score received by International Audit Offices was 3.827 with a standard deviation of 0.227. It appears that local audit organizations tend to have a higher average perception of applying machine learning in terms of perceived ease of use compared to overseas audit offices.

On the other hand, Table 7 reveals that the opinions on Perceived Usefulness for Local Audit Offices in Machine Learning have a total mean of 3.966 (SD=0.316). The overall mean score for international audit offices was 3.783, with a standard deviation of 0.430. The survey results show that the Local Audit Offices rated the International Audit Offices as more useful in the context of machine learning.

The descriptive analysis for each survey item can be found in Table 8. It compares the average of the PU and PEOU survey questions for domestic and foreign audit companies.

The item in PEOU(EBEU) had the highest mean value, with a score of 4.086 (SD = 0.366). The elements in PEOU(QOIS) and PEOU(TSSQ) also had high mean values, scoring 3.977 (SD = 0.292) and 3.930 (SD = 0.354) respectively, for Local Audit Offices. These results suggest that the respondents in this category felt it was simple to use ML systems and tools to accomplish their auditing goals.

In addition, the element in PEOU(EBEU) had the highest mean value for International Audit Offices, followed by PEOU(QOIS) with the highest mean value of 3.802 (SD = 0.360) and PEOU(TSSQ) with the highest mean value of 3.770 (SD = 0.421). This suggests that respondents in this category thought they would have no trouble picking up the use of ML systems and auditing tools, and they discovered that these resources are user-friendly.

Among the Local Audit Offices, the item in PU(TBOU) had the highest mean value of 3.961 (SD = 0.331), while the item in PU(SU) had the highest mean value of 3.972 (SD = 0.312). It appears that individuals in this group were confident that incorporating ML systems and tools would enhance their productivity in upcoming auditing tasks. Furthermore, there is an item in PU(SU) for International Audit Offices that has the highest mean value of 3.783 (SD = 0.431), along with another item in PU(SU) that has the highest mean value of 3.782 (SD = 0.429). It appears that individuals in this group believed that ML technologies and tools would be beneficial for their future auditing roles. Therefore, H1 and H2 indicate a strong belief in the user-friendliness and practicality of ML in auditing.

Table 8.
Descriptive statistics for each survey item for PEOU and PU.

	PEOU						PU			
	EBEU		QOIS		TSSQ		TBOU		SU	
	(1) Local Audit offices	**(2) Int. Audit** offices	**(1) Local Audit** offices	**(2) Int. Audit Offices**	**(1) Local Audit Offices**	**(2) Int. Audit Offices**	**(1) Local Audit Offices**	**(2) Int. Audit Offices**	**(1) Local Audit Offices**	**(2) Int. Audit Offices**
Valid	60	40	60	40	60	40	60	40	60	40
Mean	4.086	3.908	3.977	3.802	3.93	3.77	3.961	3.782	3.972	3.783
Std. Deviation	0.366	0.27	0.292	0.36	0.354	0.421	0.331	0.429	0.312	0.431

4.3. Analysis 2: Separate Specimens Perceived Ease of Use (T-Test)

The Independent Samples T-Test was conducted in accordance with Table 9 to address H3. An independent sample T-test was used to compare the significant difference in PEOU between local and international audit offices. The results displayed in Table 9 suggest that there were no significant differences in the scores for International Audit Offices and Local Audit Offices. The scores for both groups were similar, with an average of 3.827 and a standard deviation of 0.227. The magnitude of the mean differences (mean difference = 0.171, 95% confidence interval: -0.064 to 0.277) was insignificant and not significant. The results challenge the idea that local and foreign audit offices have different views on the perceived simplicity of incorporating machine learning in auditing. The alternative hypothesis cannot be accepted because there is not enough evidence. H3 is often overlooked.

Table 9.
Independent samples T-Test of PEOU.

Independent Samples T-Test							
						95% CI for Mean Difference	
PEOU	**t**	**df**	**p**	**Mean Difference**	**SE Difference**	**Lower**	**Upper**
	3.187	98	0.002	0.17126	0.05373	0.06464	0.27788

Note: at $p < 0.05$, the t-test's p-value is significant.

4.4. Analysis 3: Separate Specimens Perceived Usefulness (T-test)

An independent sample T-test was used to compare the PU between local and international audit offices in order to evaluate the hypothesis, as Table 10 illustrates.

Table 10.
Independent samples T-Test of PU.

Independent Samples T-Test							
						95% CI for Mean Difference	
PU	**t**	**df**	**p**	**Mean Difference**	**SE Difference**	**Lower**	**Upper**
	2.319	66.514	0.023	0.18383	0.07926	0.02560	0.34205

Note: at $p < 0.05$, the t-test's p-value is significant.

The results in Table 10 show that there were no significant differences in the scores for International Audit Offices (n = 40) (M = 3.783, SD = 0.430) and Local Audit Offices (n = 60) (t (df) = 66, p = 0.023). The observed mean differences (mean difference =.183, 95% CI: -.256 to .342) did not reach statistical significance. The results challenge the idea that local and foreign audit offices have different views on the effectiveness of machine learning in auditing. The alternative hypothesis cannot be supported based on the available evidence. The rejection of H4 is evident.

4.5. Type I and Type II Errors: Reporting on Non-Significant Results

Results that are statistically significant due to chance or other causes are summarized as Type I errors. A Type I error occurs when the null hypothesis is true, but it is incorrectly rejected. This type of error is also known as a false positive. On the other hand, a Type II error occurs when there is an effect present, but the null hypothesis is not rejected, leading to an incorrect negative conclusion. The probability of a Type II error is equal to the complement of the test's power. Increasing the significance threshold can lower the chances of making a Type II error. The study's findings suggest the occurrence of Type II errors, where the null hypothesis was accepted while the alternative hypotheses were rejected. Given the limited sample size and other constraints, there is not enough data to support the alternative hypotheses.

5. Contribution

This research makes a significant contribution by offering concrete evidence on how external auditors in the ARE perceive the use of machine learning. We conducted a survey to gather insights from external auditors in both local and international audit offices in the ARE. We collected data from respondents in these two types of audit offices to understand their perceptions. Analytical methods included tabulating the data, computing percentages, averages, and standard deviations, and creating graphical presentations. We also used independent sample T-tests and descriptive data analysis to assess the hypotheses.

In the future, legislators, educators, consultants, and other stakeholders will have a vital role in spearheading the transition in auditing techniques. They have the ability to create strategies, tools, and activities that improve how external auditors view the usability and simplicity of machine learning. With the expertise of a certified management accountant (CMA), the adoption of new technologies in audits can be facilitated, leading to an ultimate improvement in audit quality. This research holds great importance as previous studies did not consider the viewpoints of both domestic and international auditors in the ARE. In previous studies, there is a lack of questionnaire-based research, which could have provided a more diverse range of viewpoints. Therefore, it is crucial to address this knowledge gap by considering the viewpoints of both local and foreign external auditors in the ARE.

6. Conclusion

This study aimed to address the lack of information regarding the perceived effectiveness and ease of use of machine learning in external auditing for ARE. Based on our research, it seems that external auditors may not fully appreciate the value and simplicity of machine learning. Local audit companies view machine learning as more user-friendly. Local audit office respondents rated ML's usefulness higher than respondents from international audit offices. The findings challenge the notion that there is a disagreement between local and foreign audit offices regarding the ease of use of ML.

There are certain constraints to this research. The small sample size of 100 participants was a result of our contact methods. Less than anticipated office workers from the two groups responded. Very few staff members bothered to respond to our calls, emails, or surveys. We sometimes conducted personal interviews since machine learning in auditing is not widely recognized or commonly utilized. Given the limited sample size, it is not feasible to generalize the findings to the entire population. Additionally, the engagement rate of local audit offices was 60%, whereas overseas offices had a lower rate of 40%, which may have influenced the results in their favor. Thirdly, the study specifically examined external auditors who specialize in ARE.

Future research can explore a wide range of topics. First, researchers can collect data through in-person interviews, which offer comprehensive reports, accurate screening, and spoken data for analysis. Additionally, in order to thoroughly investigate the topics covered in this study, it would be beneficial for future research to include a wider range of research locations and data. Furthermore, future studies could explore the involvement of audit committees and internal auditors. Ultimately, conducting data collection over a longer period can lead to an increase in responses and more precise outcomes.

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