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Machine learning and external auditor perception: An analysis for UAE external auditors using technology acceptance model

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Abstract

Research Question: Do external auditors in the United Arab Emirates (UAE) perceive the ease of use and usefulness of Machine Learning (ML)?

Motivation: This study aims to investigate external auditors' perceptions of the ease of use and usefulness of Machine Learning in auditing in the UAE. In addition, the study intends to examine the difference in perceived ease of use of Machine Learning between local and international audit companies in the UAE.

Data: Data for this study were gathered from 63 external auditors working for local and global audit firms in the UAE. The study's population comprises external auditors from national and international audit companies in UAE.

Tool: The questionnaire was deployed through an online survey tool.

Findings: The results have shown that the findings do not support the idea that there is a different perception of the Perceived Ease of Use of Machine Learning in auditing between local and international audit firms. According to the conclusions of this study, external auditors have a restricted perception of the simplicity of use and utility of Machine Learning.

Practical implications: The importance of the findings of such research stems from the lack of research evidence on the perceived ease of use and usefulness of Machine Learning in external auditing in the UAE. As a result, this paper provides new empirical evidence by assessing external auditors' assessments of the usage of Machine Learning in the UAE.

Keywords: Machine Learning, Auditing, External auditors, Ease of use, Usefulness, TAM.

JEL codes: M41, M42, M48

1. Introduction

There are various benefits offered by advanced technology. These include (i) boosting revenue and raising client satisfaction, (ii) improving communication and employee retention and (iii) improving accounting performance. However, the increased dependence on advances technology has many drawbacks. These include the risk of job losses, security issues with data, and fraud (ICAEW, 2020). The development of advanced technology such as Artificial Intelligence (AI), Data Analytics, Machine Learning and Block Chain Technologies has a crucial impact on external auditors and audit firms (Noordin *et al.,* 2022). Most worldwide audit firms are attempting to focus more on modern technology to minimize the risk of audits and the chance of auditing task mistakes. It helps to increase the probability of innovation in an external audit by reducing audit risk (Bieger, 2015).

According to McGregor and Carpenter (2020), the audit profession is dealing with many difficulties in increasing audit effectiveness and quality. Audit firms have made sizable investments in implementing new technology in response to these difficulties. Although technological advancement can increase operational effectiveness and efficiency, it also introduces new risks that, if not appropriately addressed by auditors, can harm audit quality, efficiency, and professional development. An aspect of Artificial Intelligence called Machine Learning automates the development of analytical models. Machine learning uses these models to examine data, recognize trends and make predictions. As the machine is exposed to increasing volumes of data, strong pattern development and feedback is used to adjust to the behaviors. The machines are programmed to employ an iterative technique to learn from the studied data.

Machine Learning is classified into three types. First, supervised learning is one of the significant Machine Learning tasks crucial for mapping an input to an output. It also infers the function from the labelled training data. In the case of supervised learning, the pair consisting of the input object must have the desired output value (Jacky & Sulaiman, 2022). Second, unsupervised learning mainly refers to using AI algorithms by which the patterns in data sets that contain data points can be identified. It helps identify and categorize the label of data points that have data sets without external guidance. Third, reinforcement learning is one of the vital areas of Machine Learning that mainly concentrates on how intelligent agents can take actions in the environment by which the notion of cumulative reward can be maximized (Balios, 2020).

Machine Learning techniques have been used in many fields, including biology, education, health, and finance. Accounting firms are increasingly using Machine Learning because of its potential impact on auditing. Machine learning has been proven successful in providing augmented analysis to external auditors, but the fear of replacing human intelligence with Machine Learning is not taken seriously (Dogan & Birant, 2021). The ability to analyze whole datasets rather than sampling has many advantages. The technology will allow auditors to focus on outliers and anomalies, devote more time to high-risk areas, and engage in meaningful conversations, resulting in a higher-quality audit. In the following aspects, this study is different from past investigations. We investigated the perceptions of machine learning's usability and usefulness among external auditors and the differences between internal and external auditors' perceptions of these factors. Ucoglu (2020) focused on the Big Four firms and investigated the present Machine Learning applications in accounting and auditing. According to the research, the Big Four businesses created many Machine Learning tools for effective audit coordination and administration, completely automating the audit process in some areas. Fallatah (2021) reviewed relevant literature on the use of Machine Learning in accounting and assurance literature.

Handoko (2021) examined whether auditors are comfortable using Machine Learning and found evidence of auditors' readiness to use Machine Learning in corporate financial audits. Dickey (2021) indicated that although Machine Learning entails some hazards, it can significantly increase audit speed and quality. As demonstrated by Deloitte's use of Argus, a Machine Learning tool that can interpret documents, including leases, derivatives contracts, and sales contracts, the researcher claims that audit companies are already experimenting and investigating the power of Machine Learning in audits. Argus uses algorithms to recognize important contract clauses, trends, and outliers. The researcher claims that CPA firms and researchers are already looking into other applications for Machine Learning in financial statement audits, particularly in the risk assessment procedure. McGregor and Carpenter (2020) conducted a qualitative review of previous literature on the threats posed by audit firms implementing emerging technology. These threats include concerns about (1) the integrity and security of data inputs, (2) auditors heavily reliance on technology to the detriment of professional development and exercising professional judgment, (3) skills shortage, (4) the costs of technology implementation, (5) the disruptions to the audit profession's status quo, and (6) auditing standards that may be outdated.

There is a shortage of academic research on the perceptions of UAE's external auditors of Machine Learning usage and usefulness. Furthermore, data science is a conceptually and empirically fragmented emergent study subject (Frizzo-Barker *et* *al.,* 2016). Consequently, this study attempts to fill that gap by investigating external auditors' perceptions of the utility and usage of Machine Learning in external auditing in the UAE.

Our research has been conducted within the UAE environment. The UAE was the first government to appoint a Minister of State for Artificial Intelligence in 2017. The appointment coincides with the release of the government's strategic direction, which calls for the application of artificial intelligence in everything from water management to education. The UAE government has established itself as an early leader in the worldwide competition to define Artificial Intelligence. The UAE government has constructed a solid basis for incorporating AI into the fabric of public sector services, with an established commitment to foster digital innovation to improve public services and deliver better experiences.

This work adds to the existing body of knowledge on Machine Learning and external auditing. According to the conclusions of this study, external auditors have a restricted perception of the simplicity of use and utility of Machine Learning. This finding may attract the interest of academic researchers to explore similar topics in their respective countries. Regulators may find the findings of this study valuable in developing rules aimed at improving the perception of external auditors, which may lead to the proper implementation of this tool, hence, may reduce audit sampling risk and enhance audit quality.

The remaining sections of the paper are organized as follows. Section 2 reviews relevant literature and develops research hypotheses. Section 3 discusses sample selection and research design. Section 4 discusses data analysis and presents the research findings. Section 5 discuss the contributions of the study. Section 6 concludes.

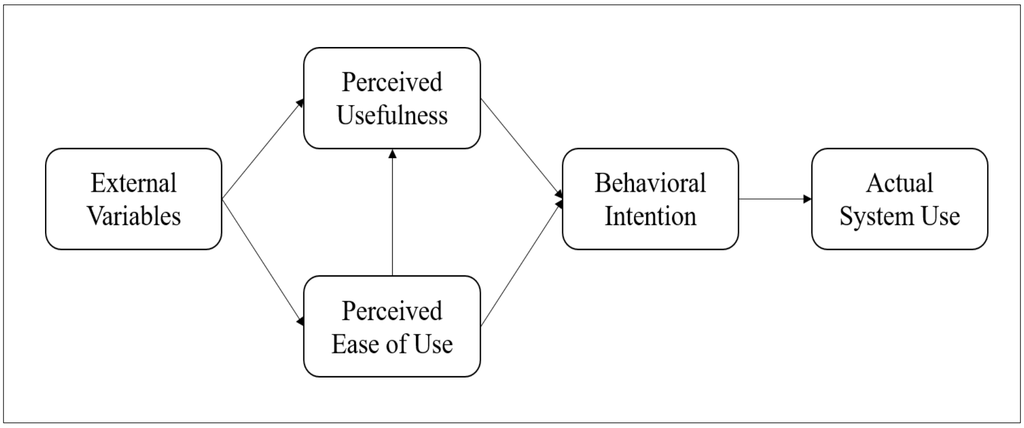
2. Literature review and hypothesis development

2.1 Theoretical framework

The Technology Acceptance Model (TAM) is an information systems theory that models how users accept and use technology. Various models have been built to evaluate and confirm the factors contributing to the acceptance of using computer technology to achieve a specific purpose (Rogers, 1995). Among those models, Figure 1 TAM by Davis (1989) was one of the most popular models that can be used to determine the explanation of acceptance towards using the technology. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are the two important determinants influencing system use. Davis (1989) explained that PEOU refers to the degree to which a person believes that using a particular system would make the task easier and avoid putting too much effort.

In contrast, PU is the tendency of people to use or not to use an application or computer technology to the extent that they trust it will help them to perform their job better and more efficiently. Thus, in this research, the PEOU and PU are the dependent variables used to measure the acceptance of using Machine Learning technology towards audit quality. The PEOU and PU of using Machine Learning will be determined among external auditors from local and international audit firms in the UAE as the independent variable.

Figure 1. Theoretical framework



(adapted from Davis, 1989)

2.1.1 Machine Learning Technology

The study of learning computer programs that employs statistics to find patterns in a massive amount of data and make precise predictions about unknown future events is identified as Machine Learning. Machine Learning techniques have been applied in many industries, including banking, health, and education (Dogan & Birant, 2021). Human-designed machine learning tools can perform various functions that can be useful to auditors and accountants. For instance, an entity's complete ledger could be audited automatically rather than sampling data (Ucoglu, 2020). Machine Learning aims to find the model that can most reliably and accurately predict future data. In order to accomplish that, algorithms are used to create mathematical models based on sample data (training data). Then, to test the data, the prediction power of the models is assessed (Ucoglu, 2020). Unsupervised machine learning is used to enhance network performance and offer services, including traffic engineering, anomaly detection, classification of Internet traffic, and quality of service improvement. Since unsupervised learning techniques have been successful in other fields, including computer vision, natural language processing, speech recognition, and optimal control, they are becoming more popular in networking (e.g., for developing autonomous self-driving cars). Unsupervised learning can also free us from the restrictions of labeled data and manually created feature engineering, enabling versatile, all-encompassing, and automated machine learning techniques (Usama, *et al.,* 2019).

Supervised learning effectively trains the input data to label the output. In this supervised machine learning, the fundamental objective is to make sense of data as per the specific question. It is the most effective category of machine learning and AI (Burkart & Huber, 2021). The concerned supervised learning can be defined as using labeled datasets to ensure that the algorithms can classify the data and predict the outcomes adequately (Balios, 2020). There are various supervised learning steps: preparing the data, choosing an algorithm, fitting with a model, choosing a validation method, examining the fit and using the fitted model for predictions (Burkart & Huber, 2021). Supervised learning can be also used for mapping an input to an output. It helps to utilize the labeled training data. The pair of input objective must have a significant value. Therefore, the algorithm can also be used to analyse the data training and produce the inferred function to ensure that the mapping is effective (Bieger, 2015). It is also appropriate for generalizing the training data as a reasonable way to ensure the effective statistical quality by which the generalization error can be avoided. Thus, supervised Machine Learning is the most advanced to utilize the algorithm of AI to make auditing decisions. It has been examined that supervised Machine Learning helps to use the data by which the algorithms can be developed based on the sample data. It is also beneficial for ensuring the predictions and decisions to enhance the explicit program to rectify any audit errors (Uddin *et al.,* 2019).

Reinforcement learning is defined as the process by which paradigms learn to recognize and extract patterns from given data (Kelleher & Tierney, 2018). It falls under the umbrella of Machine Learning. Some Reinforcement learning methods focus on finding mathematical equations to predict a result or a classification rather than using conventional statistical analysis (Dickey *et al.,* 2019). Over the past few years, Reinforcement learning has resulted in several success stories. Reinforcement learning techniques, for instance, are utilized in e-mail spam filters, credit card fraud detection, consumer segmentation in targeted advertising campaigns, and tumor diagnosis in medicine (Lantz, 2013).

The actual issue in applying Machine Learning is to identify the algorithm in which learning bias is the greatest match for a certain data set because each algorithm generalizes from a dataset differently (Kelleher & Tierney, 2018). Other names for this phenomenon are modeling bias, selection bias, and learning bias. Several models are typically developed in this step when performing data analytics with Reinforcement Learning methods, and the performance and usability are compared later. Additionally, there are two types of reinforcement learning: supervised learning and unsupervised learning. The dataset provides labelled instances with target information for supervised techniques (e.g., fraud, nonfraud, bankrupt, nonbankrupt). The question of interest is often the desired information. Each tagged example has a collection of characteristics (such as financial ratios) that are used to forecast the target data. In other words, supervised learning is predicted by applying what has been learned to a more extensive dataset after learning from examples (Provost & Fawcett, 2013).

These unsupervised techniques make it possible to build a search engine that searches quickly, requires little effort, and can be used in many other areas. Using a significant amount of unlabeled data, complicated, highly non-linear models with millions of parameters is learned using unsupervised learning techniques. Two well-known methods of unsupervised learning models are Deep Belief Networks (DBNs) and sparse coding (Khanum *et al.,* 2015).

2.1.2 Application Machine Learning in Auditing

Some studies concentrate on how auditing and machine learning work. For instance, for instance, Ucoglu (2020) noted that various fields have embraced technological advancements like Machine Learning, allowing quick and error-free data processing. As a result, Machine Learning algorithms have a lot of promise to give accountants and auditors better data analysis. Human-designed machine learning tools can perform various functions useful to auditors and accountants. For instance, an entity's complete ledger might be audited automatically rather than just a sample of the data. Some accounting and auditing tasks' mechanical and repetitive nature can be advantageous for Machine Learning applications. Automating routine accounting operations like cost reporting, managing accounts payable and receivable, and risk assessment is simple, thanks to machine learning. For instance, Machine Learning algorithms can identify the appropriate expenditure account for recognition, match a received invoice with the associated purchase order, and place the invoice in a payment pool where a human worker can review and submit the payment request to the payment queue. The Big Four accounting firms have heavily invested in technological advancements and created many platforms and products that use machine learning and artificial intelligence algorithms due to the benefits of applying machine learning approaches. There are smaller projects for accounting outsourcing services that use Machine Learning capabilities for bookkeeping or tax declaration purposes in addition to the platforms and tools that have been established.

According to Giles (2019), using technology is no longer a choice but a necessity in today's society. Technology is something that experts in any industry must follow, and auditing is not an exception. The next generation of auditors needs to be ready to work with technology successfully and efficiently as financial auditing starts to rely more on automation, artificial intelligence, and Machine Learning. First, the reliance on technology has become a near-term reality rather than a distant possibility. Almost all businesses are starting to rely on technology in some way, and they are gradually beginning to delegate the duties that once fell to entry-level accountants to the technology. This indicates that the accounting industry has changed, forcing junior accountants to learn data analysis quickly rather than data organization and processing. Future auditors must acknowledge this fact and modify their abilities to succeed. They should become proficient in the newest technologies, comprehend how well-known accounting and auditing systems function, and be able to use these systems to evaluate and translate data rapidly and effectively. To bridge the gap between executive-level accountants who have never used this technology and lower-level auditors who use it daily, auditors must also improve their communication abilities. When presenting their audit findings to their superiors, the lower-level auditors must be able to translate their knowledge into understandable terms. Instead of disappearing, auditors will continue to adapt to their surroundings as they have over the past 20 years. Artificial Intelligence and Machine Learning will fundamentally change auditors' work. It has already changed how audits work and will continue to do so soon. Ding *et al.* (2020) stated that Machine Learning techniques could benefit managers and auditors in improving accounting estimates, thereby enhancing the usefulness of financial information to investors.

Guimaraes *et al.* (2017) found that automated analyses, as opposed to manual audits, can be more reliably determined if reports comply with standardized report templates and wording. This may save much money on labor since the auditing process would no longer be done manually. According to Chi and Shen (2022), the going-concern opinions of Certified Public Accountants (CPAs) and auditors are critical. Due to errors in judgment, the failure to identify the possibility of bankruptcy can result in significant losses for corporate stakeholders and users of financial statements. Traditional statistical models are susceptible to inaccuracy and have limits when delivering going-concern assessments, which can seriously harm a company's long-term survival, growth, and investor views. To embrace the significant data era, Artificial Intelligence (AI) and Machine Learning (ML) technologies have lately been used in studies to analyze going concerns doubts and decrease judgment errors. As Giles suggested (2019), using technology is now necessary rather than an option in today's society. The shift towards technology applies to professionals in every industry, including auditing. The next generation of auditors needs to be ready to work with technology successfully and efficiently as financial auditing starts to rely more on automation, artificial intelligence, and machine learning. According to the researcher's findings, Machine Learning and Artificial Intelligence will fundamentally change how auditors perform their jobs. It has already changed how audits work today and will keep doing so for some time to come. Before beginning their careers in auditing, students must prepare for this change. The University of Tennessee is already doing an excellent job of educating students about the constantly-changing auditing industry.

As stated by Noordin *et al.* (2022), data science is an essential tool that can increase the effectiveness and cost-effectiveness of audits. Additionally, it has been demonstrated to be an effective way to lower the likelihood of human error. Data science should be considered if companies are looking for a new method to enhance their auditing procedure. The risk of a substantial misstatement must be assessed as part of the auditing process as one of the factors.

The impact of Data Analytics (DA) and Machine Learning (ML) on accounting research was evaluated by Gordon (2021). As mentioned in the paper, the intrinsic inductive character of DA and ML is causing an important trend in accounting research. This pattern involves accounting scholars using inductive-based research more frequently. Due to the recent breakthroughs with DA and ML, there is a rebalancing between inductive and deductive research in accounting. In essence, inductive-based accounting research is making a comeback. The study also includes a brief evaluation of some empirical data that corroborates the claim above.

Considering prior research, machine learning technology for auditing is still mainly in the research and development stage. Several of the larger CPA firms are developing machine learning systems, and smaller audit firms should gain as the technology's practicality improves, auditing requirements adjust, and teaching programs expand. This study looks into auditor perceptions of the usefulness and usage in the UAE. Furthermore, previous literature did not undertake empirical studies on external auditor perceptions of usefulness and usages of machine learning in the UAE. However, there is a gap in previous research to learn more about external auditors' perceptions of the usefulness and uses of machine learning. The development of new technologies such as AI and ML provides an auditor with a deeper understanding of the company's operations, allowing them to understand and assess risk potential in each audit. To maximize audit efficiency and provide the possibility of significant gains in audit speed and quality, the auditor must be aware of and up to date on this latest advanced and updated technology.

2.2 Research hypothesis development

Khanum *et al.* (2015) reported that in unsupervised learning, the patterns of untagged data are considered. It mainly involves making a combination of neural feature preferences. The spectrum of tagged and untagged data is considered, and all the accumulated data is divided into neural networks and Probabilistic methods. Under neural networks, the task gets often categorized as descriptive recognition or generative imaging process. Under this process, the computer generates information based on unsupervised and supervised data. The data entered into the system via imputes is checked by the dictionary of information already fed into the system. During the training process, the supervised network tries to mimic that available to make a correction. The energy function is a microscopic feature which measures the network's activation state. A number of approaches are getting mentioned, including clustering, learning approach and anomaly detection. Activities like hierarchical clustering, mixture model, and Expectation-minimization algorithm being followed. The cluster analysis allows unsupervised learning where each segmented data group is analyzed. Additionally, the central application of unsupervised learning is to ensure density estimation while analyzing the statistics.

As Nasteski (2017) stated, the various algorithms generate a function that maps inputs to desired outputs. The classification problem is a common way of expressing the supervised learning challenge. The learner is expected to understand a function that maps a vector into one of the several classes by examining various input-output samples of the function. Since the goal is frequently to encourage the computer to learn a classification system that had been constructed, supervised learning is the most widely used technique in classification challenges. The probability for input in supervised learning is frequently left unspecified, even when the predicted outcome is known. The output from this method is a dataset with features and labels. The main aim is to build an estimator that can forecast an object's label based on a set of features. The learning algorithm is then learnt by comparing its actual output with corrected outputs to discover mistakes after receiving a set of features as inputs along with the correct outputs. Then, it adjusts to the model appropriately.

As long as the inputs are present, no model is required, but if some of the input values are absent, no conclusions about the outputs may be drawn. The most popular method for training neural networks and decision trees is supervised learning. These two rely on the data provided by the pre-determined classification. Additionally, this learning is applied in programs that forecast probable feature events using historical data. There are numerous real-world applications of this learning, such as an application that can identify a species of iris from measurements of its blossom. In the case of network algorithms, the supervision learning process allows for measuring the outputs and making specific recommendations. They mainly include understanding the duplicate or garbage data allowing diversity in the data management process and determining data accuracy. The algorithm in supervised learning determines how the data input can be used. In addition to this supervision, learning is effective in the regression and classification of problems that have the potential to occur during the audit process. Hence, the first hypothesis is formulated as follows:

H1: There is a perceived ease of use of machine learning in auditing for local and international audit firms in the UAE.

According to Khadka *et al.* (2019), Reinforcement Learning (RL) has been successfully used for various difficult tasks, including robotic control, board games, and arcade games. Integration of RL with potent non-linear function approximators like deep neural networks is one of the factors behind the proliferation of RL applications. With the help of this collaboration, often referred to as Deep Reinforcement Learning, or DRL—RL has been effectively extended to challenges with complex input and action spaces. However, two significant obstacles prevent the widespread use of these techniques in real-world issues: (i) the difficulty of obtaining effective exploration and (ii) brittle convergence qualities, which necessitate careful hyperparameter adjustment by a designer. It enables an agent to pick up useful policies and prevents early convergence to local maxima. For DRL functioning on high dimensional action and state spaces, developing exploration tactics that produce a varied range of experiences continues to be a major problem.

The main points include the input, output, training and implementing continuous learning. The input is defined as the initial state in which the model should start. The output consists of a variety of solutions to a particular problem. The training practices are entirely based on the output, where the model attains a state in which the problem is solved more effectively. Lastly, reinforcing learning allows the best decision based on maximum learning. This learning activity is based on making decisions more sequentially. In this type of learning, the algorithm looks into the previous input's output. Therefore, it can be said that the decisions are mostly dependent. There are namely two types of reinforcement learning which include positive and negative. The positive division is the occurrence of an event due to a particular behaviour, the frequency of the same behaviour and the strength of the behaviour. This maximises performance, ensuring the implemented change stays in the memory.

On the other hand, Negative reinforcement learning is based on defining the strength of the behaviour after the negative condition has stopped. This mostly increases behaviour providing defiance, which results in a minimum performance standard. According to Ding *et al.* (2020), executive fraud interviews mandated by auditing standards could be conducted using Machine Learning technology like speech recognition. Future CPA firms can identify trends that would go unnoticed without machine learning technologies.

According to Bay *et al.* (2006), to use unsupervised methods in auditing, the results must be interpretable and intelligible and direct the auditor to specific findings for additional evaluation. According to the author, the auditor should ideally be able to comprehend why a technique flagged an input as abnormal. They address this issue by layering a supervised classifier on top of their unsupervised approach to identify qualities that contribute the most to the anomaly score. Still, they fail to give a solution in an unsupervised setting. Knowing why an entry was chosen as an anomaly can make the results more actionable for an auditor and increase their trust in a certain method. It also makes it easier for an auditor to screen out false positives before beginning a time-consuming examination.

As Choi (2021) mentioned, an audit's objective is to have a clear understanding of a company's financial activities, which can be strengthened by machine learning or reinforcement learning, as quantitative analysis is better than manual analysis. It is used to comprehend the nature of contracts and to complete analysis from start to finish without omission. Hence, the second hypothesis is formulated as follows:

H2: There is perceived usefulness of machine learning in auditing for local and international audit firms.

Kokina and Davenport (2017) suggest that machine learning and data analysis techniques are revolutionizing the auditing industry and are rapidly expanding the auditing toolkit (No *et al.,* 2019). At the same time, current methods are becoming impractical (Chiu *et al.,* 2018). Digital change is the fundamental cause of this. The business environment is being impacted by digital transformation, which affects businesses across all industries worldwide, including in the UAE. Companies produce more data as more processes switch from paper-based to digital (Reinsel *et al.,* 2018). For auditing, the expanding amount of data and operations automation constitute a particularly challenging task (Chiu *et al.,* 2018). Today, many auditing engagements still involve selecting samples of transactions to examine processes (Byrnes, 2018). The primary issue in this strategy is that it may overlook pertinent data in transactions that should have been chosen for audit. Sampling risk is what we call this. Auditors frequently select samples that are less than one percent of the data population when sampling is used (No *et al.,* 2019). This strategy becomes outdated because of the increasing amount of data, and the risk associated with sampling is increased (Chiu *et al.,* 2018). Hence, the third hypothesis is formulated as follows:

H3: There is a significant difference in the perceived ease of use of machine learning between the local and international audit firms in the UAE.

New opportunities arise as most of a company's information and data become digital. Big Four accounting firms are trying to use data analytics for auditing (Appelbaum *et al.,* 2017). These might make it possible to process the drawn samples more quickly. Additionally, they might make it possible to switch from sampling to entire population testing (No *et al.,* 2019). The objective of unsupervised learning, on the other hand, according to Chollet (2018), to discover amusing transformations of the input data without using any targets. These are used to visualize, compress, or better comprehend correlations. Unsupervised learning is exemplified through clustering. According to Aggarwal (2017), applying unsupervised Machine Learning in internal auditing is to uncover outliers and anomalies so that you may base future conclusions on them. While an anomaly is an outlier that interests an analyst, Aggarwal views outliers as all data points that could be classified as anomalies or noise from a pure data standpoint.

The purpose of utilizing an unsupervised approach was always to find outliers or anomalies (Bay *et al.,* 2006; Hagstrom *et al.,* 2018; Jans *et al.,* 2007; Kuna *et al.,* 2014; Lu *et al.,* 2006; Lu, 2007). The research identifies many reasons for attempting an unsupervised strategy, with the most frequent cause being a lack of labels or the inability to obtain them (Jans *et al.,* 2007). Another reason is that testing beyond the violation of key controls allows the auditor to check any anomalies do not violate any defined controls but may indicate concerns (Kogan *et al.,* 2014). Another benefit of employing unsupervised approaches is that previously undisclosed fraud attempts can be identified (Lu, 2007). This is in contrast to hand-crafted criteria, which are still commonly utilized in fraud detection and do not generalize to new fraud attempts (Schreyer *et al.,* 2017). Furthermore, unexpected entries and inadvertent errors can be detected (Bay *et al.,* 2006). Another argument for adopting anomaly detection in the first place is that an internal auditor may have more time for extra checks and an in-depth analysis of those abnormalities if there are fewer identified anomalies (Thiprungsri & Vasarhelyi, 2011). Hence, the fourth hypothesis is formulated as follows:

H4: There is a significant difference in the perceived usefulness of machine learning between the local and international audit firms in the UAE.

3. Research Design

3.1 Research Method

To confirm the validity of the survey questions, five auditors and three academics evaluated it. The respondents were from sixty-three external auditors in the UAE to elicit responses relevant to this research. Additionally, two external auditors who examined the questionnaire have a CPA certificate. At the same time, the other three are ACCA certified and are academics from the Department of Accounting at the Higher Colleges of Technology in the UAE. Subsequently, the questionnaires were pilot tested by five external auditors and were not part of the analyzed data. Also, some of the items' wording was slightly changed. The first part of the questionnaire reflects the qualitative characteristics of the respondents, their experience and seniority within the practice. In addition, all the respondents held positions of senior auditors, audit managers, and audit partners. Thus, six items are employed to measure the Perceived Ease of Use of Machine Learning. Moreover, another six items were developed to measure the Perceived Usefulness of Machine Learning.

This research primarily employs a quantitative approach. A questionnaire was created on a Likert scale (5 = Strongly Agree to 1 = Strongly Disagree) and consists of two main sections. The questionnaire was deployed through Microsoft forms to find respondents for our study. In the first part of the questionnaire, we looked at the demographic factors. The second part measured the perceived ease of use of Machine Learning in various local and international audit firms. The questions used were straightforward to avoid any confusion. This method was chosen due to its simplicity of implementation.

3.2 Research sample

The population of this research was represented by (63) external auditors in international and local audit firms in the UAE. External auditors have been asked several questions related to the following demographic questions:

1- To state their gender.
2- Types of qualification.
3- Years of audit experience.
4- Their current job position.
5- The type of audit firm (local or international)
6- Professional certifications.

The questionnaire was deployed through an online survey tool. As a result, 63 usable questionnaires were returned and used for the analysis; 65% of the respondents were from international audit firms, whereas 35% were from local audit firms. In addition, according to the first question, 52% of the respondents were females, while 48% were males. The majority of the respondents have a bachelor's degree of 57%, while the master's degree holders are 28%, and Ph.D. holders are the lowest at 2%. Other participants have other certificates (13%). Also, for the year of experience, 38% of the respondents have six years of auditing experience, 25% of them have from zero to two years of experience, 21% have experience of at least four years, and the rest (16%) have two years of experience but less than four years.

Regarding the fourth question, 22% of the participants work as auditor managers, while 21% work as senior auditors, 22% as auditor partners , and 35% have other job positions. Moreover, regarding professional certifications, 11% of participants held a CPA certificate, 19% had ACCA certificates, and 3% of the respondents held CIA certificates. The study shows that 51% of external auditors' participants hold other professional certifications, and 14% of external auditors have local certificates.

3.3 Data collection method

An online survey tool was created, and the link was distributed among the survey participants. The participants are either audit partners, audit managers, senior auditors or personnel authorized in this field from local and international audit firms in the UAE. The kind of questions where the participants would answer either agree, strongly agree, disagree, strongly disagree, or have a neutral opinion. The following questions in Table 1 were used to determine the Perceived Ease of Use and Usefulness of Machine Learning. The survey items were adapted from (Albawwat & Frijat, 2021 and Noordin *et al.*, 2022).

Table 1. Items for perceived ease of use and perceived usefulness of machine Learning

Item Code	Items for PEOU of Machine Learning (ML)
PEOU 1	Learning to operate ML systems and tools in auditing would be easy for me.
PEOU 2	I would find it easy to get ML systems and tools to do what I want to do in auditing.
PEOU 3	My interaction with ML systems and tools in auditing would be clear / understandable.
PEOU 4	I would find ML systems and tools in auditing to be flexible to interact with.
PEOU 5	It would be easy for me to become skillful with ML systems and tools in auditing.
PEOU 6	I would find ML systems and tools in auditing easy to use.
Item Code	**Items for PU of Machine Learning (ML)**
PU 1	Using ML systems and tools in my future auditing job would enable me to accomplish tasks more quickly.
PU 2	Using ML systems and tools would improve my future job performance in auditing.
PU 3	Using ML systems and tools in my future auditing job would increase my productivity.
PU 4	Using ML systems and tools would enhance my effectiveness of the job in auditing.
PU 5	Using ML systems and tools would make it easier to do my future job in auditing.
PU 6	I would find ML systems and tools useful in my future job in auditing.

4. Data analysis and findings

4.1 Validity and reliability test of the instrument

To validate the reliability of the survey items, we examine Cronbach's Alpha value using the unidimensional reliability test. Twelve (12) survey items were tested, including 6 items from PEOU and 6 from PU. The result of the alpha in the reliability test was 0.96, as in Table 2, which indicated that the survey items are valid and reliable, considering the value of Cronbach's Alpha is at the proficient level.

Table 2. Validity and reliability test

Cronbach's Alpha	Number of Items
0.96	12

4.2 Analysis 1: descriptive analysis of PEOU

Descriptive statistics consists of frequencies and percentages for two categories ordinal and nominal data. Moreover, descriptive statistics include averages such as mean, median, ranges, and standard deviations for continuous data. Frequency is defined as several participants that can fit into a specific group or category. It helps to recognize the percentage of the sample that corresponds with that group and category. The percentage has been calculated to determine the percent of the sample that corresponds with the given frequency. Normally, the average that is calculated is the mean. Mean illustrates the average unit for a continuous item. Standard deviation describes the spread of those units to reference the mean.

Table 3. Perceived ease of use and perceived usefulness

Descriptive Statistics				
	PEOU		PU	
	(1) Local Audit Firms	(2) Int. Audit Firms	(1) Local Audit Firms	(2) Int. Audit Firms
Valid	22	41	22	41
Mean	3.788	3.602	4.008	3.813
Std. Deviation	0.831	0.887	0.803	0.762

The data was collected from respondents of two types of audit firms in the UAE that consist of 1-Local Audit Firms (n=22) and 2-International Audit Firms (n=41). In addition, to address H1 and H2, the descriptive statistics in Table 3 represent the Machine Learning perceptions on Perceived Ease of Use for Local Audit Firms reporting an overall mean score of 3.788 (SD=0.831). For International Audit Firms, the score is 3.602 (SD=0.887). This demonstrates that Local Audit Firms have a higher mean than International Audit firms towards the perception of using Machine Learning under Perceived Ease of Use.

As stated by the Telecommunications and Digital Government Regulatory Authority, Machine learning is an integral element of artificial intelligence (AI) focusing on developing the learning capabilities of technological advancements. The advancement of machine learning technology has been contributing to its broader application in various fields, including the audit field. This trend aligned with the UAE Digital Economy Strategy launched in March 2022 (Telecommunications and Digital Government Regulatory Authority, 2022). In this context, it is possible to expect the integration of AI and ML into external audit processes.

On the other hand, Table 3 also shows that Machine Learning perceptions on Perceived Usefulness for Local Audit Firms reveal an overall mean of 4.008 (SD=0.804). For International Audit Firms, the overall mean score is 3.813 (SD=0.762). This illustrates that respondents from Local Audit Firms have assigned the highest rating to the perceived usefulness of machine learning to the International Audit Firms.

Table 4 shows the descriptive analysis for each survey item. It compares the mean between the PEOU and PU survey items between local and international audit firms.

The item in PEOU3 had the highest mean value of 3.909 (SD = 0.921) for Local Audit Firms, indicating that the respondents from this category had the perception that it was easy to get ML systems and tools to do what they wanted to do in auditing. At the same time, the item in PEOU5 had the highest mean value of 3.683 (SD = 0.934) for International Audit Firms for International Audit Firms. This indicates that respondents from this category had perceptions that learning to operate ML systems and tools in auditing would be easy for them, and they found that ML systems and tools in auditing are easy to use. The item in PU2 had the highest mean value of 4.318 (SD = 0.945) for Local Audit Firms, indicating that the respondents from this category found that using ML systems and tools in their future auditing job would increase productivity. At the same time, item in PU2 had the highest mean value of 3.902 (SD = 0.917) for International Audit Firms. This indicates that respondents from this category had perceptions that they found ML systems and tools sound in their future job in auditing. Hence, H1 and H2 indicate that there is a Perceived Ease of Use and Perceived Usefulness of Machine Learning in auditing for each type of audit firm.

Table 4. Descriptive statistics for each survey item for PEOU and PU

	PEOU3	PEOU5	PU2	PU2
	(1) Local Audit Firms	**(2) Int. Audit Firms**	**(1) Local Audit Firms**	**(2) Int. Audit Firms**
Valid	41	22	22	41
Mean	3.909	3.683	4.318	3.902
Std. Deviation	0.921	0.934	0.945	0.917

4.3 Analysis 2: Independent samples T-Test – perceived ease of use

To answer H3, the Independent Samples T-Test was performed as reported in Table 5. An independent sample T-test was conducted to compare the significant difference in PEOU between Local Audit Firms and International Audit Firms. The result shows in Table 5 that there were no significant differences (t (df) = 61, p = .42) in scores for Local Audit Firms (n = 22) (M = 3.79, SD = 0.83) and International Audit Firms (n = 41) (M = 3.60, SD = 0.89). The magnitude of the differences in the means (Mean difference = 0.186, 95% CI: -0.272 to 0.645) was small and insignificant. The findings do not support the idea that there is a different perception of Perceived Ease of Use of Machine Learning in auditing between local and international audit firms. There is not enough evidence to accept the alternative hypothesis. Thus, H3 is rejected.

Table 5. Independent samples T-Test of PEOU

Independent Samples T-Test							
						95% CI for Mean Difference	
	t	df	p	Mean Difference	SE Difference	Lower	Upper
PEOU	0.812	61	0.420	0.186	0.229	-0.272	0.645

Note: p-value associated with the t-test is significant at p < 0.05

4.4 Analysis 3: Independent samples T-Test – perceived usefulness

To test the H4, an independent sample T-test was conducted to compare the PU between Local and International Audit Firms as shows in Table 6.

Table 6. Independent samples T-Test of PU

Independent Samples T-Test							
						95% CI for Mean Difference	
	t	df	p	Mean Difference	SE Difference	Lower	Upper
PEOU	0.948	61	0.374	0.195	0.205	-0.216	0.605

Note: p-value associated with the t-test is significant at p < 0.05

The result shows in Table 6 that there were no significant differences (*t* (df) = 61, p = 0.347) in scores for Local Audit Firms (*n* = 22) (*M* = 4.008, *SD* = 0.803) and International Audit Firms (*n* = 41) (*M* = 3.813, *SD* = 0.762). The magnitude of the differences in the means (Mean difference = .195, 95% CI: -.216 to .605) was small and insignificant. The findings do not support the idea that there is a different perception of the Perceived Usefulness of Machine Learning in auditing between local and international audit firms. There is not enough evidence to accept the alternative hypothesis. Thus, H4 is rejected.

This study follows the direction of the Financial Audit Government Working Group meeting, which was held as part of the Second UAE Government Annual Meetings in Abu Dhabi that emphasizes the importance of conducting the necessary specialized and technical research for the implementation of Artificial Intelligence (AI) in auditing procedures and operations (Ministry of cabinet affairs, 2018).

This study's findings align with those of (Avian Accounting,2020), who indicated that auditing departments in Dubai, UAE, will have to assess new risk classes with new threats such as e-commerce and social media platforms. With new AI technology integrated into enterprises, financial and accounting data would face even more significant risks and challenges. Auditors must stay as near to the potential hazards of contemporary technologies. According to (Avian Accounting, 2020), the auditing function in Dubai, UAE will have to deal with not only digital financial data but also AI-powered data. Businesses will soon automate regular bookkeeping tasks such as journal entries of accounting transactions. Machine Learning will significantly accelerate the processing of data recordings. We have already seen the impact of Machine Learning on other commercial domains, such as autonomous translations and customer support duties.

Our findings are in line with prior research. The results are in line with those of Dickey *et al.* (2019), who stated that Machine Learning could significantly increase audit speed and quality. Machine Learning employs models to analyze data to detect trends and make predictions. The machines are programmed to employ an iterative approach to learn from the studied data, making learning automated and continuous; when the machine is exposed to increasing volumes of data, robust patterns emerge, and feedback is used to modify actions. Our findings are also in line with Kokina and Davenport (2017) and Raphael (2017). Kokina and Davenport (2017) found that the Big four companies were utilizing AI and machine learning. At the same time, the authors found that the application of the new technology could increase the risks of bias. Raphael (2017) showed that the technologies were ensuring vital progress in the field. The studies show the perspectives of international auditors demonstrating primarily positive perceptions with a moderate level of risks. Although Hoogduin (2019) concluded that Machine Learning approaches are not often applied in financial statement audits, our findings are not in line with this conclusion.

4.5 Reporting on non-significant results: Type I and Type II errors.

Type I summarises the results that are statistically significant because of unrelated factors or by chance. Also, Type I error rejects the null hypothesis when it is true. In addition, a Type I error is considered a false-positive conclusion.

Meanwhile, the Type II error failed to terminate when there was an effect. However, Type II error is a false negative conclusion. The probability of type II error is equal to one minus the power of the test. Moreover, Type II error can be decreased by increasing the significance level. Type II error is caused by the less powerful test or small sample size and appears when the acceptance levels are too inflexible.

In this research, the findings are towards the Type II error where the alternative hypotheses were rejected, and null hypotheses were accepted. There is not enough evidence to support the alternative hypotheses due to the small sample size and other limitations.

5. Contribution

As a result, the research's first significant contribution is that it provides empirical data by examining the perceptions of external auditors in the UAE regarding using Machine Learning. We surveyed to gather information about external auditors' perceptions of Machine Learning in the UAE. To analyze the perception of external auditors in the UAE, data was collected from respondents of two types of audit types in the UAE, which are local audit firms and international audit firms. As for the analytical tools, we used descriptive data analysis and independent sample T-test to test the hypotheses, tabulating the data, calculating percentages, averages, standard deviations, and graphical presentation.

Policymakers, trainers, consultants, and others will play a significant role in leading the change in auditing practices in the future. They can create programs, tools, and activities to improve external auditors' perceptions of Machine Learning's ease of use and usefulness, allowing them to use new technology in the auditing process and eventually enhance audit quality. The final implication is to assist future researchers because previous studies lack the perspective of UAE-based auditors, both local and international. The studies also lack questionnaire-based research, which would ensure a broader range of opinions. As a result, it is critical to close the research gap by investigating the perceptions of international and local external auditors in the UAE.

6. Conclusion

The primary goal of this study was to address the shortfall of research evidence on the Perceived Ease of Use and Perceived Usefulness of Machine Learning in external auditing in the UAE. According to our findings, external auditors have little knowledge of the perceived ease of use and usefulness of Machine Learning. We discovered that local audit firms have a slightly higher perception of perceived ease of use of machine learning. Furthermore, respondents from Local Audit Firms gave Machine Learning the perceived usefulness the highest rating compared to International Audit Firms. The findings do not support the idea that there is a different perception of the perceived ease of use of Machine Learning in auditing between local and international audit firms.

There are several limitations to this study. First, due to our communication method, we had a small sample size (63 participants). Responses from local and international audit firms in the UAE were lower than expected. Few employees responded to our emails, phone calls, or completed our survey. As a result of ongoing pandemic constraints and a lack of transportation, we only had one mode of communication. As a result, we were unable to conduct face-to-face approaches between the researcher and employees of audit firms in the UAE. As a result of small sample size, results are not generalizable to the entire population.

Second, there is a low participation rate among local firms and a high participation rate among international audit firms. Employees of local firms participate in the survey at a rate of 30%, while employees of international firms participate at a rate of 70%. As a result, the limitation of dominating the opinion of international firms arises. Third, this research is explicitly conducted from the perspective of an external auditor working in the UAE.

There are several potential future research opportunities. First, future research can change when the world comes out of the pandemic. Hence, the qualitative data using interviewing techniques and a survey of at least a hundred participants can be executed to overcome the limited communication methods and the low sample size. Furthermore, researchers can use the interview approach as a data collection tool. The face-to-face interview provides accurate screening, captures verbal data for word analysis, and assists in the creation of a more detailed report.

Second, future studies may investigate the issues addressed in this study by using different research sites and a broader range of data. We suggest including additional audit and business companies in future research to broadly test the hypothesis. Third, future research could include other stakeholders, such as audit committees and internal auditors. Finally, future research may extend for a longer period of data collection to obtain more responses and for more precise and accurate results.

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