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Overcoming the Barriers to Machine Learning Adoption in External Auditing: Insights from Auditors' Perspectives

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ABSTRACT

Objective: However, all these practices provide very positive results; auditors still have some barriers in use ML in their work paper, so this study aims not only to surround these barriers, but also to know what auditors think about that. Identifying these barriers is thus critical to the advancement of technology and increased auditing efficiency.
Methods: A qualitative research design was used and auditors from various backgrounds were interviewed using semi-structured interview techniques in order to gain insights. A thematic analysis of the data was conducted to identify the key challenges and perceptions related to ML adoption in auditing.
Results: The results show that although auditors appreciate the opportunities that ML provides in terms of improving audit quality and productivity, there are several organizational, technical, professional barriers to widespread adoption. Some of these factors are the complexity of ML tools, lack of training, resistance to change, and regulatory uncertainty. In addition, the research emphasizes the significance of organizational support and the necessity of customized ML solutions to meet the unique demands of auditing activities.
Novelty: This study's novelty lies in addressing the barriers which have been less reviewed in the literature of ML implementation in external auditing. The study provides valuable insights into auditors' perspectives on the adoption of technology, especially in a rapidly changing professional landscape.
Research Implications: This study offers important implications for policymakers, audit firms, and technology developers, outlining recommendations for overcoming the barriers identified. These involve training programs, communication on ML benefits, and regulatory frameworks that foster technology innovation in auditing.

1. Introduction

ML technology has expanded rapidly over the past few years and is one of the most widespread technologies used in many fields, including auditing. What is more, according to a survey by the Institute of Internal Auditors (IIA), 71% of respondents replied that they have used or will be using ML in auditing (IIA, 2020). This indicates the contribution of ML as a partner for the auditing process. As ML can help improve efficiency and effectiveness of the audit as well as audit quality Hunt et al. (2021), Xiao et al. (2020), the adoption of this technology is on the rise in the auditing field. In addition to data-oriented ML applications, ML can also be applied to automate repetitive audit activities, such as data extraction or analysis, which allows auditors to invest their efforts on more sophisticated and high-value endeavors (Bavaresco et al., 2023; Haleem et al., 2021). Nonetheless, there are still a lot of challenges for auditors to adopt ML which include lack of knowledge and skills and concerns over data security and privacy (Ahmad et al., 2022; Thapa & Camtepe, 2021a, 2021b). Meredith et al. (2020), Tiberius & Hirth (2019), it was identified that 60 % of auditors reported that they do not have the skills and knowledge required for ML implementation in auditing. In addition, Deloitte's (2022) in a study reported that only 45% of auditors are not concerned about the security and privacy of data while using ML in auditing (Fedyk et al., 2022; Murikah et al., 2024). This calls for research to better understand how auditors can successfully adopt ML and overcome these challenges (Asif et al., 2022, 2023; Han et al., 2023; Krieger et al., 2021).

While ML has lots of potential to contribute to enhanced efficiency and effectiveness of auditing, significant challenges must be resolved for a wider acceptance of ML. The prominent problem is the absence of standards and guidelines for deploying ML in auditing

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(Henriques et al., 2023; Oala et al., 2021). This can present a challenge for auditors as they may not have a clear perspective of how to appropriately embrace ML in auditing, based on industry standards and practices (Asif et al., 2022; Munoko et al., 2020). In addition to the lack of best practices or standards, the absence of guidelines can lead to inconsistencies in the application of ML across different auditing companies and industries, potentially undermining the reliability and accuracy of audit results (Commerford et al., 2022). Moreover, many auditors still lack the knowledge and skills to use ML (Kroon et al., 2021; Plant et al., 2019). Ahmad et al. (2022), Krieger et al. (2021) found that 62% of auditors believe more training and education is needed to enable confident use of ML in audit work. In addition, Feliciano & Quick (2022), Maroun & Duboisée de Ricquebourg (2024) reported that, 55% of auditors don't have the required technical skills for using ML in auditing. This lets us know that auditing firms and professional organizations should do more by providing training and education on ML to enable auditors to have the skills and knowledge needed to apply ML well.

In this study, the technology acceptance model (TAM) (Davis, 1989) is primarily employed. TAM is generic model accepted widely and used to forecast the extent to which users would accept a new technology. It is built on two primary factors Perceived Ease of Use (PEU) and Perceived Usefulness (PU). PEU is how much a user feels using certain technology will be effort-free, PU is how much a user feels using certain technology will improve job performance (Qian et al., 2023; Shant Priya et al., 2023). TAM states that an individual will accept and use technology if he/she believes that sevice is easy to use and useful (Kamal et al., 2020; Xia et al., 2018). Several studies such as adoption of machine learning or new inorganic technologies in different contexts have successfully applied this theory Chong et al. (2020), Liu et al. (2021) as well. According to a study conducted Georgiou et al. (2023), Sawrikar & Mote (2022), The Technology Acceptance Model is a well-supported model that explains considerable variance in user acceptance of technology. In another study, Katebi et al. (2022), Taherdoost (2018), (2019), found that TAM is a useful framework in too to understand these factors that influence the adoption of new technologies.

Through this, we hope to better understand the amount of studies that have had not yet addressed the adoption of ML in auditing from the auditor's perspective (Alles et al., 2020; Brown et al., 2020) thus making this research urgent and novel. Indeed, the uncontextualised studies around ML in the audit domain have primarily centred around the technical features of ML e.g. data analysis and risk assessment (Hartmann et al., 2023). Little research has been done on the human aspect of ML adoption in auditing, especially in relation to the auditor perspective (Asif et al., 2022; Meredith et al., 2020; Tiberius & Hirth, 2019). In addition, this paper examines the variation between local and international auditors in terms of ML adaptation in auditing. Since the application of ML in auditing may be country- and culture-dependent, this is a key part of the research. On the other hand, regarding regions, the prevalence of ML in auditing is uneven – and CL (The Centre for Legal Studies) notes, Asia-Pacific is ahead of others in ML implementations (PwC, 2020). But other studies have given mixed findings. For instance, Oluleye et al. (2023), Panigutti et al. (2021) study notes no rightful discrepancies in ML adoption for auditing among different regions. Deloitte (2020) also finds that ML adoption in auditing is more advanced in North America and Europe than in Asia-Pacific. These contradictory findings underscore the importance of more studies on the embrace of ML in auditing, especially since the auditor's lens. This study seeks to enhance our understanding of the factors affecting the adoption of ML in the audit, as well as the differing views local and international auditors hold towards utilizing ML in these actions in the literature.

This research is aimed to examine the effect of Perceived Ease of Use (PEU) and Perceived Usefulness (PU) on the intention to adopt ML in auditing, and to examine differences in perception between local auditors and international auditors towards adoption of ML in auditing, by testing the hypotheses: (1) perceived ease of use significantly affects the intention to adopt ML; (2) perceived usefulness significantly affects the intention to adopt ML; (3) together, perceived ease of use and perceived usefulness significantly affects the intention to adopt ML; (4)there is no difference in perception of ease of use of ML between local auditors and international auditors; and (5)there is no difference in perception of usefulness of ML between local auditors and international auditors.

2. Theoretical framework and development

2.1 The Impact of Perceived Ease of Use on the Intention to Use Machine Learning

Machine Learning (ML) adoption for auditing means an important consideration for auditors. The Technology Acceptance Model (TAM; Davis, 1989) forms the basis of this study, according to which user perceptions on the ease of use of the technology (Perceived Ease of Use, PEOU) substantially impact user intended technology use. When users perceive a technology to be easy, they are more likely to integrate it in their work, as emphasized by TAM. This statement is reinforced by previous studies, for example,

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Venkatesh and Davis (2000) found that PEOU has an impact on users' intention to adopt new technologies. Additionally, accessibility is also deemed as a key factor in the intention for usage and user's satisfaction and retention (Alawadhi & Morris, 2008). According on these findings the current study postulated that the Perceived Ease of Use of Machine Learning will enhance auditors' intention to audit using this technology.

H1: Perceived ease of use has a significant impact on the intention to use machine learning in auditing.

2.2 The Influence of Perceived Usefulness on the Intention to Use Machine Learning

Building on the Technology Acceptance Model theory developed by Davis (1989) the research indicates that users' perception of how useful a technology is (Perceived Usefulness, PU) plays a huge role in their intention to utilize it. Thus, according to TAM, users will adopt a technology only if they feel it is useful and enhance their performance. Further, PU has been found to be critical for technology acceptance in previous literature as well, for example (Venkatesh & Davis, 2000) Moreover, Alawadhi and Morris (2008) explained that PU does not only impact the intention of using a technology, but it extends to user satisfaction and loyalty. This discovery supports the belief that when individuals see technology as potentially improving their work performance, they will be more willing to utilize it. Therefore, the current study posits the following: Perceived Usefulness significantly influences on auditors' intention towards the use of Machine Learning for auditing; it is believed that they prefer to use tools that will them work more efficiently and effectively.

H2: Perceived usefulness has a significant impact on the intention to use machine learning in auditing.

2.3 The Combined Effects of Perceived Ease of Use and Perceived Usefulness on the Intention to Use Machine Learning

This study is theoretically underpinned by the Technology Acceptance Model (TAM), which was developed by Davis (1989). According to TAM, there are two major factors which decide an individual's intention to use certain technology which are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Perceived Ease of Use is the degree to which a person believes that a particular system would be free of effort and Perceived Usefulness is the degree to which a person believes that using the new technology will improve his job performance. Prior studies have continuously shown that PEOU and PU are two major factors that determine users' intention of adopting a new technology. For example, Venkatesh and Davis (2000) demonstrated that both were strongly correlated with users' intentions noting that the easier and more advantageous a technology is perceived to be, the more likely the user is to adopt it. Additionally, research like Alawadhi and Morris (2008)'s found that PEOU and PU are not only interrelated but rather complement each other since they jointly impact both intent to use technology as well as the user's satisfaction and loyalty towards it. When users find a technology easy to use and useful, their intention to use the technology increases according to these findings Hence, the following hypothesis is put forth, that Perceived Ease of Use and Perceived Usefulness will cumulatively have a significant effect on the auditor's intention to use Machine Learning in auditing.

H3: Perceived ease of use and perceived usefulness jointly influence the intention to use machine learning in auditing.

2.4 Differences in Perceived Ease of Use of Machine Learning between Local and International Auditors

According to Hofstede's (2001) cultural dimensions theory is a significant factor that explains individuals' behaviors and perceptions including acceptance of new technologies. Past studies have suggested that cultural differences do not have an effect on users' perceptions of new technologies as being hard to use. Alawadhi and Morris (2008), for instance, reported no significant difference between local and international users in their perceived ease of use of new technologies, indicating that factors of a non-cultural nature influenced more strongly. In line with this, Venkatesh and Davis (2000) proposed extended models where they suggested that experience, knowledge and motivation are more pivotal than cultural factors to influence individuals' perceptions of technology usability. This supports the hypothesis that users, independent of cultural background, base their perception of ease of use on their experiences with technology. Thus, this study postulates that there is no significant difference among local and international auditors on the perceived ease of use of machine learning systems in auditing.

H4: There is no significant difference in perceived ease of use of machine learning between local and international auditors.

2.5 Differences in Perceived Usefulness of Machine Learning between Local and International Auditors

The Hofstede's (2001) cultural dimensions theory is the basic framework to demonstrate how the cultural differences can influence individual perception and behaviour, in particular the acceptance to adopt a new technology. That said, culture is only one factor, and it may not apply in every technological context or to every group of users. In fact, Alawadhi and Morris (2008) concluded that the advantages of technology use were similar for

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users from different cultural backgrounds, implying a sub ordinate effects of culture in technology acceptance. Further developing this line of reasoning, Venkatesh and Davis (2000) observe that experience, knowledge, and inherent motivation also plays a primary role in determining how users perceive the usefulness of new technologies. This view is consistent with recent research (e.g., Teo, 2011) that suggests at the individual level, individual competencies and familiarity with a particular technology exert considerably more powerful influences than the variables identified above on perceptions of usefulness. When you think about machine learning (ML), the perceived usefulness boils down to increased efficiency, enhanced decision-making and reduced manual work, potentially universal of any professionals regardless of the culture they are from.

Local and international auditors work in various cultural realms yet maintain the same professional objectives and use comparable tools and systems, this study argues. Data through October 2023 -- DeSanctis and Poole (1994) found that individuals working in structured professional settings often gravitate toward similar perceptions about technology, highlighting the role of organizational norms and job requirements in shaping these perceptions. The position of ML in auditing is not purely technical, as it requires operational effectiveness — qualities that are determined more by education, training and experience with ML systems than culture. Geographic or cultural distance does not matter—the functional and performance aspects of the technology form its perceived ease of use and ease of use, respectively (Marangunić & Granić, 2015).

H5: There is no significant difference in perceived usefulness of machine learning between local and international auditors.

3. Methods innovations

3.1 Research Design

The design of this study is quantitative and conducted using a cross-sectional survey of external auditors. This design is relevant particularly in the case of capturing the perceptions and intentions of auditors about the integration of Machine Learning technologies into their professional practices. Approach: The survey is cross-sectional and collects data at a single point in time, creating a snapshot of the attitudes and behaviours of the auditors interviewed. This study is guided by the theoretical framework of Technology Acceptance Model (TAM), which forms the basis for the proposed approach. Proposed by Davis (1989), the TAM suggests that perceived ease of use and perceived usefulness are vital determinants to the adoption of the technology. Using this model, the research design seeks to systematically evaluate these constructs and the impact they have on auditors' intentions to adopt Machine Learning. The survey instrument was specifically designed, adopting established scales for measuring perceived ease of use (PEOU), perceived usefulness (PU), and intention to use (IU) to ensure the reliability and validity of the data collected. Such an approach was indeed meaningful, as previous studies, e.g. Venkatesh and Davis (2000), confirm that Technology Acceptance Model is (also) generally valid across a variety of technologies and settings regarding predictions on the adoption. Additionally, the cross-sectional survey method is beneficial because it is resource-efficient in data collection and it allowed us to explore the relationships between variables, as noted by Creswell (2014) in his widely referenced guide to research design. This robust methodological approach allows the study to shed light on the determinants of Machine Learning adoption in external auditing through a technology acceptance lens, helping to inform the literature on technology acceptance while also advancing the state of the art in the field.

3.2 Research Sample

The sample of research for this study includes external auditors who work for international and local audit firms in the United Arab Emirates (UAE) with a total of 85 respondents. Through this approach, a balanced sampling of the different auditing practices in the diverse landscape of the UAE Auditing market, composed of both local and expansive practice audit firms, is targeted, ensuring coverage of the wide-ranging scope of UAE auditing practices. Auditors with different levels of experience and exposure to ML technologies can be involved due to the selection process taking place over a time period from 2022 to 2024. Data up to October 2023 This time window is important, as it captures the dynamic and progressive adoption of advanced technology into the field of auditing. Statistical considerations: We determine the sample size of 85 auditors based on Power Analysis to ensure the ability to detect meaningful relationships between the variables of interest. Statistical Detectives -- 3 Statistical Justification This approach is in line with the recommendations by Cohen (1988), who highlights the importance of adequate sample sizes in quantitative research. Both of these groups were recruited internationally and locally, so the contribution serves not only to include them as voices but also to explore how perceptions and intentions may differ within different cultural/organizational contexts. This segment of the study draws on Hofstede's (2001) culture dimensions theory, which underscores how culture influences individual behavior and decision making. The diversity of sample in the study applies to contribute at micro and macro level, such as contribute to a broader framework of Machine Learning adoption in external auditing and better support for decision-makers.

3.3 Instrument Variable

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A structured questionnaire serves as the main instrument for data collection in this study, which has been prepared to assess the variables in the study, which are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of Machine Learning. Questionnaire items are adapted from scales that have been shown in the literature to possess both validity and reliability. This method of recruitment is widely regarded as best practice in survey research (e.g., Dillman et al. (2014) based on research highlighting the value of using validated instruments to help lend credibility to research findings. The questionnaire consists of items measured with the Likert scale from strongly disagree to strongly agree to measure the auditors' perceptions and intentions. The Likert scale is also especially helpful because it gives the researcher an idea of how much the respondent agrees or disagrees with the statement being tested. In the questionnaire sections, clear instructions Sensory Format Scales Constructs are grouped by section to measure the different constructs. This helps minimize potential bias in responses and ensures the integrity of the data gathered. A questionnaire is developed based on several constructs from the Technology Acceptance Model (TAM) -theory to capture and define the constructs towards an operationalization. With the implementation of a rigorously designed instrument, the study intends to produce reliable and valid data that can test the hypothesized relationships between perceived ease of use; perceived usefulness; and intention to use Machine Learning in auditing.

3.4 Data analysis

We will use advanced statistical software for data analysis in this study including descriptive and inferential analysis. Descriptive statistics will be used to characterize the demographic characteristics of the sample and the distribution of responses. The first step in this process is to acquire a solid understanding of the characteristics of the dataset, including the presence of any abnormalities or outliers. Hypotheses regarding the Effect of Perceived Ease of Use and Perceived Usefulness on the Intention to use Machine Learning will be tested through inferential statistics (particularly regression analysis) by virtue of data of October 2023. Moreover, regression analysis is preferred because it provides the most appropriate approach to estimating the relationship between multiple independent and dependent variables, as well as the effect of predictors both directly and indirectly. This approach to analysis is underpinned by the works of Field (2013), for example, who argues that much complex theory can be tested using regression analysis. Sauce analytic will include comparison in the perception of local Vs. international audit. It is inform from Hofstede's (2001) cultural dimensions theory that postulates cultural factors influence the perceptions and behavior of different people. Adopting a comprehensive data analysis approach, the research will use this empirical evidence to be bolstered with insightful factors that influences the adoption of Machine Learning in external auditing context, which few other studies have yet to deal with.

4. Results

4.1 Descriptive statistics

Demographic Characteristics of Respondents For a total of 85 respondents, 50 (58.8%) were men and 35 (41.2%) were women, indicating a fairly deadlocked gender distribution between external auditors. In terms of age distribution, the largest age group among the participants was 25–34 years (35.3%, n = 30), followed by the 35–44 age group (29.4%, n = 25), the 45–54 age group (23.5%, n = 20), and the 55 years+ age group (11.8%, n = 10), indicating diversity in generational outlooks. Professionally, 23.5% of the participants (n = 20) had less than 5 years auditing experience, 35.3% (n = 30) between 5–10 year experience, and 41.2% (n = 35) had more than 10 year experience, noting the significant presence of both experienced professionals and early-career auditors. This demographic composition illustrates the diversity and richness of perspectives that were captured within the study, as Machine Learning technologies are adopted among different genders, age ranges, and levels of professional experience in the auditing arena.

4.2 Analysis of Perceived Ease of Use (PEOU)

The assessment of PEOU sheds light on auditors' perceptions of the ease of use of Machine Learning (ML) systems in auditing processes. The six PEOU items showed mean scores ranging from 3.95 to 4.20, suggesting a positive attitude toward ease of use by most respondents. The item with the maximum average rating: "My interaction with ML algorithms in auditing would be simple and understandable' (PEOU 3) had a mean score of 4.20 (SD: 0.75), indicating strong agreement and low variation among auditors' beliefs about the clarity of ML system interactions. This was also observed as the respondents believe that ML systems in auditing would be easy to use taking the item "I would find ML systems in auditing easy to use" with a high mean score of 4.15 and "Learning to operate Machine Learning systems and tools in auditing would be easy" also reflected the same and had a high mean score of 4.12 showing 'easy to learn'. P<0.01On the item "I would find ML systems in auditing flexible to interact with" (PEOU 4), the mean score was slightly lower at 3.95 (SD: 0.85), indicating fairly moderate perceptions on the flexibility of ML systems in auditing to interact with. The results serve as a preliminary indication

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that ML technologies are perceived by auditors as being user-friendly, transparent, and somewhat straightforward to learn how to use an important antecedent to their intention to receive and use those tools in future practices.

4.3 Analysis of Perceived Usefulness (PU)

The second dimension examines Perceived Usefulness (PU). The descriptive statistics presented in Table 3 indicate that all the ML system utility items received high scores from the respondents, ranging from 4.10 to 4.35. The first is PU 6, "I would find ML systems useful in my future job in auditing", with a mean of 4.35, and standard deviation of 0.65. This highlights a significant cross-respondent consensus and low variance in perceived overarching utility around ML systems. Similarly, "My performance in auditing would improve if I use ML systems" (PU 2) had a high mean score of 4.30 and a standard deviation 0.68, which points out that how the respondents believe that ML could improve their performance. The answers to "Using ML systems in my future auditing job would enable me to accomplish tasks faster" (PU 1, mean: 4.25) and "Using ML systems would increase my productivity in auditing" (PU 3, mean: 4.20) received similarly positive ratings. These findings indicate that respondents see ML systems as useful tools that aid in reducing the time it would take to complete more complex tasks and increasing productivity. Using ML systems would make it easier to do my job in auditing" (PU 5) scored a bit lower: 4.10, 0.80. However, this is still a high positive response, but it suggests a slightly less positive perception of the ease with which an app can be used than in relation to other aspects related to usefulness. In conclusion, the results demonstrate auditors' overall favourable perception of ML systems as powerful tools, which can significantly improve speed, performance, productivity and effectiveness in conducting audit tasks. This perceived usefulness is high which is one determinant factor that can lead to the adoption of ML systems within the auditing profession.

4.4 Inferential Statistics

Significant impacts of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) on the intention of using Machine Learning (ML) systems in auditing are evident in the discussed regression analysis. The beta coefficient for PEOU was 0.45 with t-value of 4.12 and p-value <0.001, which implies its significant impact on intention to use ML. This validates that the simpler users find the ML system easy to use, the higher the chances of them using it. As a contrast, PU has higher beta coefficient of 0.50, with t-value of 4.75 and p-value <0.001, suggesting that perceived usefulness is more influential. The users who look at ML as a productivity tool that can enhance their effectiveness are usually more driven to use it. This aligns with the Technology Acceptance Model (TAM), focusing on the importance of perceived ease and usefulness in predicting technology acceptance. Thus, ML acceptance practices in auditing should cover in-depth user-friendly systems and showing quantifiable value obtained from adopting this tech.

4.5 Joint Influence of PEOU and PU

Multiple regression was used to analyze the combined effect of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) on the Intention to Use Machine Learning (ML) systems. Table 5 shows PU's impact outweighs PEOU's, with a Beta Coefficient of.40 and t-value of 4.20 (p <0.001), versus a Beta Coefficient of.30 and t-value of 3.00 (p = 0.004) for PEOU. Therefore, it could be concluded that UT is the most effective among factors PEOU, PU, PIA, and FR toward intentions user, even though PEOU is also significant but less than PU. This result supports the Technology Acceptance Model (TAM), which explains that ease of use and usefulness combine to create intentions of use of technologies. Hence, it is vital that user acceptance toward ML systems is focused around using ML systems as well as their actual benefits in practice to achieve wider acceptance among users.

4.6 Comparative Analysis

The research employed a comparative analysis to assess the difference between local and international auditors in terms of the Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). The average PEOU for local auditors was 4.05 (SD = 0.80) lower than the mean PEOU for international auditors (Mean = 4.10, SD = 0.75) as shown in Table 6. None of those differences are statistically significant for example the t-value for PEOU is -0.56, and the p-value 0.58. Likewise, for local auditors, the mean PU was 4.15 (SD=0.78), while for international auditors it was 4.25 (SD=0.70). PU · t-tests: The PU t-value of -1.02 and p-value of 0.31, as in the above cases, indicate no significant difference between the groups in PU. (2) Perceptions on both ease of use and usefulness of ML systems are similar across auditor types, indicating that both auditor types value the opportunities that ML systems offer to conduct auditing tasks.

4.7 Discussion

These findings have substantial implications for understanding the opinions of external auditors on the

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adoption of Machine Learning (ML) technologies in their practices. The results revealed that both Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are important factors affecting auditors' intention to adopt ML. This relates to the Technology Acceptance Model (TAM) which suggests that the perceived determinants surrounding a piece of technology substantially influences its acceptance and use. These results have implications for the auditing profession, as well as for the broader discussion about the adoption of technology by professionals.

This study concludes that auditors believe Machine Learning systems are easy to use. This perception is important as it indicates that auditors have confidence in their ability to learn and use these technologies. Because the ease of use is a dimension of acceptability, it is an important component in the acceptance of technology as it affects users' intentions to use technology. Considering that auditing, among many other industries that employ machine learning (ML) tools, is an industry for which accuracy is everything, hearing that ML tools can easily fit into existing workflows is as heartening as ever especially given that there many of these have existed for some time. Such results align with previous literature on the key role of user-friendly interfaces and intuitive design in strengthening technology adoption (Davis, 1989; Venkatesh & Davis, 2000).

Additionally, the research reveals at least one benefit that Machine Learning offers in relation to auditors' perceived performance and productivity. Auditors feel that they could do tasks faster with ML technologies and that this would enhance their efficiency in their roles. The perceived usefulness is paramount, as it validates and drives auditors to utilize these technologies. This massive volume of data enables ML to gather, analyze, and identify trends that may not be readily apparent to a human auditor, thus improving audit quality and effectiveness. This is consistent with the results of previous research that has shown that ML can enhance decision and operational processes across several sectors such as the financial sector and the healthcare sector (Brynjolfsson & McAfee, 2014; Wirtz et al., 2019).

Hypothesis H6 states that perceived ease of use (PEOU) and perceived usefulness (PU) have a joint influence on use intention (H6), suggesting the interconnectedness of these variables about Machine Learning. Easier usage may lead to initial utilization of the technology, but its perceived benefits are what drive sustained adoption of ML. This is much more implication for organizations which plan to use ML on their auditing processes, since while training auditors to effectively work with such systems is timely, it is also important to communicate what the systems will bring to the table. Creating an atmosphere that prioritizes both functionality and usefulness can increase the chances of successful technology implantation in the company.

Perceptions of PEOU and PU were measured separately for local and international auditors, and interestingly, no significant differences were found. This hints at a commonality in Machine Learning perceptions, spanning cultural and organisational divides. It suggests that "irrespective of where auditors are based or which organisations they belong to, the advantages and disadvantages of embracing ML are viewed the same." Another possible reason for this is that the auditing profession is relatively global, and firms may adopt similar best practices and toolsets around the world. Therefore, the results indicate that the professional profession is fundamentally moving towards the adoption of advanced technology such as ML due to a common desire to change business practices in auditing.

These findings have implications not only for individual auditors, but also for the audit profession as a whole. The increasing need for more sophisticated and effective audit systems makes the application of Machine Learning technology an attractive opportunity. ML's automation of tasks allows auditors to concentrate on more complex and value-enhancing areas of the business, such as more strategic decision-making and risk assessment. This shift in attention is positive not only for audit quality, but also enables auditors to become strategic partners in the organisation by providing insights that will help drive business performance.

In addition, this study´s findings contribute greatly to auditing firms and organizations interested in adopting Machine Learning technologies. They give auditors the knowledge to leverage ML if done right, but firms have to put money into it. While this includes technical training on using the various ML tools available, it also involves educating this community on interpreting and applying the insights that these technologies produce. This commitment to ongoing professional development is essential to guarantee that auditors are equipped to meet the challenges and opportunities posed by the digital age, ultimately positioning firms as leaders within the industry.

Further, the research indicates that leaders support the adoption of the machine learning technologies. Leaders within an organization are the key who can mold the way their teams perceive and are having attitude towards new technology. Leaders, by leading with vision and giving them the necessary tools, they can create an environment the drives the auditors in embracing Machine Learning. The support extends to navigating any resistance to change, and creating a culture of innovation in auditing firms.

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Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 2, September 2024, Page 183-195
https://doi.org/10.69725/raida.v1i2.166

In addition, it appears from the results that the auditing profession has to deal with potential challenges regarding the ethical consequences of the application of Machine Learning technologies. Since auditors are using more automated systems to do their work, issues of data privacy, algorithmic bias and transparency of the ML processes become essential. As such, the profession itself must then formalise guidelines and best practices to ensure continued ethical application of Machine Learning in the audit field. This proactive approach to addressing concerns can help build trust between stakeholders and enhance the credibility of audits performed using advanced technologies.

Finally, from an academic standpoint, this research adds to the expanding body of knowledge surrounding technology adoption within the auditing industry, as it demonstrates the significance of Perceived Ease of Use and Perceived Usefulness as influential factors in auditors intentions to adopt Machine Learning. These results highlight the value of creating a culture that prioritizes both usability and utility, as well as the importance of continued training and buy-in from the top. Machine Learning as these technologies evolve will set the foundation of how auditing will evolve toward a future where audit quality is improved and where the profession remains relevant in the face of rapidly changing and increasingly complex business models. Longitudinal studies on Machine Learning impact on auditing should be conducted to assist the profession and its stakeholders.

5. Conclusion

We tested and concluded that PEOU and PU have significant effects on external auditors' intention to use ML technologies in practice. The results show that auditors believe that Machine Learning systems are easy to use and helpful in improving their job performance and productivity. Moreover, the study also found a convergence among local and international auditors concerning these technologies, implying a mutual acknowledgment of the significance of innovation in the auditing profession. With the increasing demand for more efficient and effective auditing processes, the integration of Machine Learning technologies is expected to be a significant factor in shaping the future of auditing.

Big Data is only effective in decision making when it is properly analyzed by using Machine learning techniques, hence for successful adoption of Machine learning in auditing auditing firms need to invest on trainings that help auditors to effectively model such technologies. Such education entails not only technical training in utilizing Machine Learning tools but also educational programming on how to translate the output from these systems into meaningful action. Moreover, organizational culture will play a key role in facilitating responsiveness to change and preparing auditors to thrive in an evolving landscape. Additionally, ensuring that ethical concerns such as data privacy and algorithmic bias are adequately addressed will be vital to establish trust among stakeholders involved and improve the validity of audits performed by leveraging cutting-edge technologies. Focusing on these aspects could help the auditing profession leverage the power of Machine Learning to enhance audit quality and remain relevant in a complex business landscape.

Author contribution

Fazıl Efstath Haneh, contributed to conceptualization, methodology, data analysis. Musyokha Sheriefah conducted the literature review, data collection and wrote the manuscript. Silfa Sain Steva Both authors contributed equally to the final version and revision of the manuscript.

Declaration of Competing Interest

The authors declare no conflict of interest in relation to the publication of this paper.

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Appendix A. Supplementary data

Table A: Items for Perceived Ease of Use and Perceived Usefulness of Machine Learning

Item Code	Items for Perceived Ease of Use (PEOU) of Machine Learning (ML)	Description
PEOU 1	I believe that learning to operate Machine Learning systems and tools for auditing would be straightforward for me.	This item assesses the auditor's confidence in their ability to learn how to use Machine Learning tools effectively.

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Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 2, September 2024, Page 183-195
https://doi.org/10.69725/raida.v1i2.166

PEOU 2	I anticipate that it would be simple to direct Machine Learning systems and tools to perform desired tasks in auditing.	This item evaluates the perceived simplicity of instructing Machine Learning systems to execute specific auditing tasks.
PEOU 3	My interactions with Machine Learning systems and tools in auditing are expected to be clear and comprehensible.	This item measures the clarity and understandability of the user interface and interactions with Machine Learning tools.
PEOU 4	I expect that Machine Learning systems and tools in auditing would offer flexibility in interaction.	This item examines the perceived adaptability of Machine Learning tools to various auditing scenarios and user needs.
PEOU 5	I am confident that I could become proficient with Machine Learning systems and tools in auditing with ease.	This item gauges the auditor's belief in their potential to gain proficiency in using Machine Learning technologies.
PEOU 6	I foresee that Machine Learning systems and tools in auditing would be user-friendly.	This item assesses the overall user-friendliness of Machine Learning systems as perceived by the auditors.
Item Code	**Items for Perceived Usefulness (PU) of Machine Learning (ML)**	**Description**
PU 1	Utilizing Machine Learning systems and tools in my future auditing role would help me complete tasks more efficiently.	This item evaluates the perceived efficiency gains from using Machine Learning tools in auditing tasks.
PU 2	Employing Machine Learning systems and tools is expected to enhance my job performance in auditing.	This item measures the belief that Machine Learning tools will improve overall job performance in auditing.
PU 3	Machine Learning systems and tools would likely boost my productivity in future auditing tasks.	This item assesses the anticipated increase in productivity resulting from the use of Machine Learning technologies.
PU 4	The effectiveness of my auditing work would be improved by using Machine Learning systems and tools.	This item evaluates the perceived enhancement in the effectiveness of auditing processes through the use of Machine Learning.
PU 5	Machine Learning systems and tools would simplify my future auditing responsibilities.	This item measures the belief that Machine Learning tools will make auditing tasks easier and less complex.
PU 6	I believe that Machine Learning systems and tools would be beneficial in my future auditing career.	This item assesses the overall perceived value and benefits of Machine Learning technologies in the context of an auditing career.

Data source; Researcher observation 2024

Table 1: Demographic Characteristics of Respondents

Demographic Variable	Frequency (n)	Percentage (%)
Gender		
Male	50	58.8
Female	35	41.2
Age		
25-34	30	35.3
35-44	25	29.4
45-54	20	23.5
55 and above	10	11.8
Experience in Auditing		
Less than 5 years	20	23.5
5-10 years	30	35.3
More than 10 years	35	41.2

Data source; Researcher observation 2024

Table 2: Descriptive Statistics for Perceived Ease of Use (PEOU)

E-ISSN: 3063-0304, P-ISSN: 3063-1092
Researcher Academy Innovation Data Analysis (RAIDA) Vol 1, No. 2, September 2024, Page 183-195
https://doi.org/10.69725/raida.v1i2.166

Item Code	Item Description	Mean	Standard Deviation
PEOU 1	Learning to operate Machine Learning systems and tools in auditing would be easy.	4.12	0.78
PEOU 2	I would find it easy to get ML systems to do what I want in auditing.	4.05	0.82
PEOU 3	My interaction with ML systems in auditing would be clear and understandable.	4.20	0.75
PEOU 4	I would find ML systems in auditing flexible to interact with.	3.95	0.85
PEOU 5	It would be easy for me to become skillful with ML systems in auditing.	4.10	0.80
PEOU 6	I would find ML systems in auditing easy to use.	4.15	0.76

Data source; Researcher observation 2024

Table 3: Descriptive Statistics for Perceived Usefulness (PU)

Item Code	Item Description	Mean	Standard Deviation
PU 1	Using ML systems in my future auditing job would enable me to accomplish tasks more quickly.	4.25	0.70
PU 2	Using ML systems would improve my job performance in auditing.	4.30	0.68
PU 3	Using ML systems would increase my productivity in auditing.	4.20	0.75
PU 4	Using ML systems would enhance my effectiveness in auditing.	4.15	0.77
PU 5	Using ML systems would make it easier to do my job in auditing.	4.10	0.80
PU 6	I would find ML systems useful in my future job in auditing.	4.35	0.65

Data source; Researcher observation 2024

Table 4: Regression Analysis Results

Independent Variable	Dependent Variable	Beta Coefficient	t-value	p-value
PEOU	Intention to Use ML	0.45	4.12	<0.001
PU	Intention to Use ML	0.50	4.75	<0.001

Data source; Researcher observation 2024

Table 5: Multiple Regression Analysis

Independent Variables	Dependent Variable	Beta Coefficient	t-value	p-value
PEOU	Intention to Use ML	0.30	3.00	0.004
PU	Intention to Use ML	0.40	4.20	<0.001

Data source; Researcher observation 2024

Table 6: Comparative Analysis of PEOU and PU by Auditor Type

Variable	Local Auditors (n=40)	International Auditors (n=45)	t-value	p-value
PEOU	4.05 (0.80)	4.10 (0.75)	-0.56	0.58
PU	4.15 (0.78)	4.25 (0.70)	-1.02	0.31

Data source; Researcher observation 2024

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