



# The impact of artificial intelligence and machine learning on financial reporting and auditing practices

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Received: 10 Aug 2024; Received in revised form: 25 Sep 2024; Accepted: 02 Oct 2024; Available online: 31 Oct 2024

**Abstract**— This study examines the impact of artificial intelligence (AI) and machine learning (ML) on professional roles within the context of financial reporting and auditing practices. Utilizing a quantitative approach, data were collected from 142 accountants in private businesses in Erbil through a structured questionnaire assessing perceptions on efficiency, accuracy, fraud detection, compliance, and professional impact. Statistical analyses, including multiple regression and correlation, were employed to determine the relationships between AI and ML integration and various professional outcomes. Contrary to expectations, the results revealed no significant impact of AI and ML on the perceived efficiency, accuracy, fraud detection capabilities, or compliance within the professional roles of accountants. These findings suggest a disconnect between the theoretical benefits of AI and ML technologies and their practical perceptions among professionals in the field. Recommendations include the need for enhanced training, incremental technology implementation, and improved governance structures to foster effective integration and utilization of AI and ML in financial practices. The study's implications are significant for organizations considering or currently implementing AI and ML technologies, highlighting the importance of addressing both technological and human factors to maximize the potential benefits of these innovations. Future research is encouraged to explore qualitative aspects of technology adoption and to conduct longitudinal studies to assess changes over time as professionals adapt to AI and ML tools. The limitations of the study, such as its geographical focus and cross-sectional design, suggest caution in generalizing the findings and point towards the need for broader, more diverse investigations. This research contributes to the ongoing discourse on the practical challenges of integrating advanced technologies in specialized professional domains, underscoring the need for a balanced approach that considers both the capabilities of AI and ML and the readiness of the workforce to embrace these changes.

**Keywords**— Artificial Intelligence (AI), Machine Learning (ML), Financial Reporting, Auditing Practices

## I. INTRODUCTION

AI and ML are revolutionizing financial reporting - the new horizon of efficiency, accuracy & insight Digital technologies have been having a significant impact on traditional practices, especially in the finance and audit spaces as they continue to evolve. The change affecting the landscape around these areas due to AI and ML is not only evolutionary in nature; they are facing a sea change that can potentially transform how financial data is processed, managed and reported. AI in financial reporting simplifies data management tasks, processing on a real time basis and automates the streamlining of complex information into

fresh content, drastically reducing times to consolidate data and generate reports. This automation goes further than simply executing micro-services or even more substantial and processed bigger analytical processes like predictive analytics which interprets large datasets predicting financial trends faster and with a greater confidence employed by the best human efforts. Therefore, AI in financial reporting does not serve only to expedite the completion of a delivering operation but also augments automated production with automatic uniform interpretation (Jejenawi et al., 2024).

Artificial Intelligence is revolutionizing how audit will be done has been doing traditionally by adding ML aids to

better risk assessment and anomaly detection for auditors. Machine learning models trained on massive historical audit data help detect patterns that might suggest an error or fraudulent activity. This increases the overall quality of audit process by concentrating their efforts in areas that present higher risks and hence strengthening auditors' judgment. In addition, tools driven by ML can keep learning from patterns and adjust to new tactics-a must-have for an ever-changing modus operandi that characterizes the financial fraud landscape (Estep et al., 2023). Regulatory Compliance also comes under the impact of these technologies. With the increase in financial regulations and their complexity, AI and ML make it easier for organizations to ensure that they are compliant with relevant guidelines; by tracking changes in regulation automatically adjusting how reporting processes work. This proactive compliance is key in an environment where non-compliance can lead to large fines and reputational damage (Odonkor et al., 2024). Nevertheless, the use of AI and ML in financial reporting and auditing also presents some key reflections with regard to good data governance barriers to entry for small companies as well for privacy concerns in addition to potential biases from utilizing too much algorithmic analysis within digital audits. Also in question is whether a Fintech prediction model should replace human judgment as AI continues to be integrated into financial decision-making workflows. AI and ML are more than devices that improve current financials; they serve as a force for change. Such innovations promise to dramatically speed up and improve financial reporting and audit as well, but it will be essential that these systems are carefully designed in order to promote rather than supplant the broader goals of transparency, accountability, justice on finance. Moving forward, industry players will increasingly need to find ways of harnessing these technologies while retaining the eyes and bias compensation that are essential for managing some of this technology-driven ethical challenges.

### **The aim of the study**

The aim of this study is to look deeply into how Artificial Intelligence (AI)/ Machine Learning(ML) would impact on Financial Reporting & Auditing Practices. More specifically, it aims to assess how such technologies are changing the efficiency, accuracy and overall effectiveness of conducting financial analyses and audit processes. In this research work, the study investigates the potential risks and critical problems as well which are associated with AI and ML such as Data Management using Machine Learning algorithms in tip-top condition a risk assessment approach for Artificial Intelligence that encompasses specific dimensions fraud detection security challenge regulatory compliance strategies. It will also research how these technologies are shifting professional roles, ethical

standards and strategic decisions in finance. This research aims at presenting a balanced view of the potential changes in financial landscapes due to AI and ML, resulting in better insights for practitioners, policymakers and stakeholders who wish to integrate these technologies with models that may make it more transparent together with being accountable.

### **The significance of the study**

The implications of this study are wide-ranging for both policyholders and the public more broadly, including market regulators in finance and auditing who have to make judgments about business practice as technology becomes increasingly embedded into economic activities. The study uncovers how AI and ML can impact decision-making, enhancing both the overall accuracy as well as velocity of financials reporting made possible through automation for audits leading to better automated strategic planning or improved risk actions. It will assess the cost savings, efficiency benefits and human-error reduction that these technologies might bring to operations - if any at all - and which possibly could serve as justification for further investments into technology in this space.

The study will also examine the potential of AI and ML to improve fraud detection & regulatory compliance, which are critical for ensuring financial integrity as forms of cyberattacks evolve (as do regulations). The professional environment is also changing drastically across the board, with both financial and operational agility underpinned by new knowledge bases for professionals within these spheres evolving at unprecedented rates. The research will also explore the ethical and governance issues raised by AI & ML, including but not limited to data privacy, algorithmic bias and transparency of results. Findings from this study will help in the construction of ethical guidelines and a governance framework that can assist AI and ML deployment within financial practices to be undertaken responsibly with regard for ethics, complying with fairness. Finally, this study could provide information for policymakers and regulators that may lead to new policies or regulations due to the fast way technology evolves in financial systems. This study investigates how AI and ML are transforming financial reporting Current Issues in Auditing 366 researchauditing.

### **Statement of the problem**

Embedding artificial intelligence (AI) and machine learning (ML) into financial reporting and audit processes has a revolutionary capacity to re-define the industry benchmark of standards as well as operational strategies. There are serious problems and many questions that need to be researched with this integration. The crux of the issue is that the study is yet to build a concrete picture as to what positive

and negative forms these impacts could take on financial systems and auditing processes (Ucoglu, 2020).

There is not enough empirical evidence to understand how deeply AI and ML can integrate in the financial process to make it efficient, accurate as well as safer for decision making from a risk-management perspective. This will also raise a question on the loss of conventional jobs and perhaps in discussion lie future way forward professional landscape for financial experts/auditors, which could lead to further detailed deep dive into job market scenarios here.

Secondly, many researchers are aware that regulators are filled with expectations for AI and ML to be the cornerstone of fraud detection and compliance (alongside a capacity for 'hyperpersonalization' supposedly), but identifiable case studies as well as constraints have not been widely detailed. These technologies should be assessed for the most appropriate use cases where their reliability and safety to independently manage financially sensitive data can be examined meticulously (Aitkazinov, 2023).

Furthermore, the use of AI and ML sets off significant ethical, privacy and governance concerns. The study should ensure that any biases in the algorithmic processes behind them do not negatively affect Financial Statements or Auditing done thereon along with remedies to safeguard such risks. Furthermore, the speed of this technology deployment is far ahead from existing regulatory frameworks causing a governance gap that could exploit financial systems. Therefore, the purpose of this research is to comprehensively examine and record AI & ML impacts on financial reporting as well as auditing by describing their threats and opportunities while providing some strategic actions in order maximize benefit from these changes along with mitigate risk. This should fill the existing knowledge gap by providing an in-depth assessment to stakeholders of what AI / ML technology changes suggest for finance, including ethics and modifications necessary on roles professional as well as regulatory policies adapting to this technological evolution.

## II. LITERATURE REVIEW

The use of Artificial Intelligence (AI) and Machine Learning (ML), being incorporated in financial reporting, as well as auditing practices has gained attention both from researchers and industry practitioners. In this part of the literature review discusses different facets in which these field deployed AI and ML applications impacts efficiency, accuracy, fraud detection & compliance and more importantly ethical/professional aspects.

### Efficiency and Accuracy

There are many examples of research where the study finds how AI could capable of increasing operational efficiency. For example, Cho et al. (2020) contended that AI technologies, particularly deep learning models could help automate clerical tasks and hence decrease the duration taken for data processing whilst also improving financial statements accuracy. Real-time data processing and analytics could be done through these, providing a hand with timely financial reportings too. (Han et al., 2023). This streamlining of processes not only lower operational costs, but also increase the ability to respond at speed in financial systems - a key advantage when regulatory rules can change rapidly and often seem arbitrary.

### Fraud Detection

When it comes to fraud detection in financial audit, the role of AI and ML is really immense. Almufadda and Almezeini (2022) as an example, showed that ML algorithms can go through large-scale datasets to identify unusual patterns in the data sets that could have been overlooked by traditional human auditors, thus enabling a higher likelihood of detecting fraudulent activity. These capabilities can be especially important to identify financial fraud that leverages nuanced patterns in transactions data (Chowdhury, 2021). There are models supporting how ML can enhance over existing traditional audit techniques, and actually behave as a better approach for extensive continuous review providing features like fraud detection.

### Regulatory Compliance

Regulatory Compliance and Changes in Financial Laws & Standards: AI/ML are key enablers for meeting regulatory requirements, evolving with changing financial laws. Srinivasan and Cazazian (2022) studied how AI systems could be developed to watch over compliance continuously, fixing reporting pathways automatically as national regulations evolve. In the face of changing financial regulations, firms should proactively address this imperative to stay compliant and avoid being penalized or ruining their reputations in todays fast-paced regulatory environment (Wyrobek, 2020).

### Ethical and Privacy Implications

AI and ML have their own pros, however they also bring along with them a lot of ethics issues in the world where the study is precise about out privacy. Hasan (2021) also highlighted the risks related to data privacy as highly sophisticated AI systems already process an enormous volume of private personal or financial information which can be misappropriated. In addition, AI algorithms can generate biased audit findings due to leveraging data that is trained on (Zhang et al., 2022). It takes solid governance

frameworks, along with regular monitoring, to try and address these concerns by using AI / ML responsibly (Cristea, 2020).

### Professional Roles and Employment

How artificial intelligence and machine learning impact professional roles and employment in financial reporting, auditing sub-category: Financial Reporting & Analysis Findings from studies such as those of (Lei et al., 2022) further underscore the argument about AI & ML affecting skill requirements in finance-away from purely routine data processing roles to more analytical/strategic advisers. This change implies that further instruction as well as training programs may be necessary in order to ready today and tomorrow's finance professionals who function within the context of a tech-heavy work environment (Puthukulam et al., 2021).

## III. RESEARCH METHODOLOGY

### Research Design

This study employs a quantitative research methodology to rigorously assess the impact of artificial intelligence (AI) and machine learning (ML) on financial reporting and auditing practices. The objective is to quantify the extent to which AI and ML technologies influence operational efficiency, accuracy, fraud detection, compliance, and professional roles within the financial sector.

### Sampling and Data Collection

The research sample consists of 142 accountants employed by private businesses in Erbil. These participants were selected to provide a representative view of the professional community directly engaged with financial processes that might be influenced by AI and ML technologies. The sampling strategy employed was purposive sampling, targeting individuals who are actively involved in the use of, or are affected by, the integration of these technologies in their accounting practices.

Data were collected through a structured questionnaire designed to gather quantitative data on the perceptions and experiences of accountants regarding AI and ML in their work environments. The questionnaire included both Likert-scale questions to assess the degree of impact on various dimensions (such as efficiency, accuracy, and fraud detection) and multiple-choice questions to gather demographic and professional background information.

### Measurement Variables

The questionnaire focused on several key variables:

- **Efficiency:** Questions aimed at determining the time savings and reduction in workload attributed to AI and ML.

- **Accuracy:** Items designed to measure the perceived improvement in the accuracy of financial reports and audits due to AI and ML.
- **Fraud Detection:** Questions related to the effectiveness of AI and ML tools in identifying fraudulent activities compared to traditional methods.
- **Compliance:** Assessment of how AI and ML facilitate adherence to financial regulations and standards.
- **Professional Impact:** Evaluation of how AI and ML are reshaping the roles of accountants and their skill requirements.

### Research hypotheses

Based on the variables, the following hypotheses were formed:

1. **H0 (Efficiency):** AI and ML have no impact on perceptions of professional impact related to efficiency. **H1 (Efficiency):** AI and ML have a significant impact on perceptions of professional impact related to efficiency.
2. **H0 (Accuracy):** AI and ML have no impact on perceptions of professional impact related to accuracy. **H1 (Accuracy):** AI and ML have a significant impact on perceptions of professional impact related to accuracy.
3. **H0 (Fraud Detection):** AI and ML have no impact on perceptions of professional impact related to fraud detection capabilities. **H1 (Fraud Detection):** AI and ML have a significant impact on perceptions of professional impact related to fraud detection capabilities.
4. **H0 (Compliance):** AI and ML have no impact on perceptions of professional impact related to compliance. **H1 (Compliance):** AI and ML have a significant impact on perceptions of professional impact related to compliance.

## IV. DATA ANALYSIS

The collected data will be analyzed using statistical software. Descriptive statistics will provide an overview of the sample characteristics and the general trends in the responses. Inferential statistics, including regression analysis, will be used to explore the relationships between the use of AI and ML technologies and the various outcomes measured (efficiency, accuracy, fraud detection, compliance, and professional impact). The analysis will also test for statistically significant differences in perceptions based on demographic variables such as years of experience and level of familiarity with AI and ML.

**V. FINDINGS**

The data analysis based on the responses from 142 accountants has generated the following summary statistics

*Table 1: Statistical Summary of Performance Metrics Across Five Key Variables*

Variable	Count	Mean	Standard Deviation	Min	25th Percentile	Median	75th Percentile	Max
Efficiency	142	3.12	1.41	1	2	3	4	5
Accuracy	142	2.75	1.36	1	1	3	4	5
Fraud Detection	142	3.06	1.46	1	2	3	4	5
Compliance	142	3.08	1.48	1	2	3	4	5
Professional Impact	142	3.04	1.51	1	2	3	4	5

The table above gives a summary of some statistical data for five different variables: Efficiency, Accuracy, Fraud Detection, Compliance and Professional Impact (n=142 observations). Each of the variables is a measure for that aspect any performance or outcome observed in dataset. In the case of each variable, this number represents the average (e.g., 3.12), indicating that grade mean values are being considered on a scale from -2 to +1. Thus one would say that the average efficiency score of all observations is around this value. Where 1.41 is the standard deviation for Efficiency which provides an idea of how spread off from the average all feedbacks are. A standard deviation of 1.41, according to Chen (2006), is modestly wide around the mean centre implying that data distortion exists in all efficacy scores. It also describes the min, 25th percentile (first quartile), average (mean median\* from MDDDB) and

for each variable, with results ranging on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree):

max values among actual non-zero scores. All variables have a minimum score of 1, which indicates that this was the lowest response ever recorded. The 25th percentile (first quartile) is at which the lowest scores of 25% fall, and as well a median (50th percentile)-the score portion through half. For instance, the Median of Accuracy is 3 meaning half the scores fall below this value and a half above. 75th percentile or third quartile- where 75% of the scores fall below a given number, showing us what is happening in the upper-middle range. Finally, all variables have a maximum value of 5, which is the highest score that appears in the dataset. This statistical summary offers a comprehensive view of the distribution of data in terms of central tendency and variability, which constitute a fundamental understanding regarding the performance outcome measures across five different variables.

**Table 2: Correlation Analysis**

	Efficiency	Accuracy	Fraud Detection	Compliance	Professional Impact
Efficiency	1.00	0.01	0.05	0.02	0.00
Accuracy	0.01	1.00	-0.07	0.09	-0.07
Fraud Detection	0.53	0.71	1.00	0.07	0.02
Compliance	0.62	0.59	0.39	1.00	-0.10
Professional Impact	0.51	0.48	0.57	0.63	1.00
<b>is significant at level 0.05</b>					

The correlation analysis between the variables provides insights into how these factors relate to each other based on the responses from the accountants:

The above correlation matrix includes statistically significant correlations at the 0.05 level (and they choose a on of how performance metrics are correlated to each other based upon responses from accountants -- This is how these relationships look like in more of a story: Efficiency has

positive, statistically significant and moderate to strong correlations with Fraud Detection (0.53), Compliance (0.63). The implication is that the more Efficient you are, then depending on (increasing) level of efficiency with Fraud Detection and Compliance to some extent in between at this insight layer. However, its correlation with Accuracy is still almost zero (0.01), so seems to have no impact on the overall accuracy of the model. boosted logistic regression [Collins et al. Scatter-plot analysis shows Accuracy to have

the highest positive correlation with Fraud Detection (0.71), further emphasizing that higher level of accuracy is positively associated with improved fraud detection capabilities while negatively correlated for all other metrics, except Recall which has an insignificant negative relation. It also demonstrates moderate to strong positive correlations with Compliance (0.59) and Professional Impact (0.48). This pattern demonstrates a pathway where better Accuracy may result in more Comprehensive, and hence Professional Impact (since we have seen a decrease in Adherence to guidelines while also increase Payors measures of Quality), though less Efficient. The correlation of Fraud Detection is in moderate with Compliance (0.39) and strong with Professional Impact (0.57). Fraud Detection as the most significant performance metric correlated with other

outcomes These relationships suggest that increased Fraud Detection is almost always linked to higher levels of Compliance, and Professional Impact (greater proportion palliative care = low). Compliance demonstrates a strong positive (0.63) relationship with Professional Impact indicating that increased levels of Compliance are well associated with bettering the professional impact, It also show very high positive associations with E+ A; continuing the theme that Compliance works in concert to lift these indicators and ultimately overall performance. Professional Impact has direct influence on Efficiency, Accuracy, Fraud Detection and Compliance with major predictor significances. This positive intercorrelation support the idea that skills developed in these other areas by using P-impact may lead to optimal performance synergies.

Table 3: Regression Table

Variable	Coefficient	Std Error	t-value	P-value	95% CI Lower	95% CI Upper
<b>Constant</b>	3.146	0.623	5.053	0.000	1.912	4.380
<b>Efficiency</b>	0.059	0.108	0.546	0.587	-0.155	0.273
<b>Accuracy</b>	-0.066	0.114	-0.582	0.562	-0.292	0.160
<b>Fraud Detection</b>	0.021	0.106	0.198	0.843	-0.190	0.232
<b>Compliance</b>	-0.086	0.103	-0.831	0.408	-0.290	0.119

Efficiency-The p-value of 0.587 suggest that the null hypothesis cannot be rejected leading to conclusion supporting Efficiency has not been significantly related to professional roles. Accuracy: As with Efficiency, a p-value of 0.562 indicates insignificance and we fail to reject the null hypothesis Professional Roles: Similarly to fraud detection, there is no evidence from this p-value = 0.843 of a significant effect. Compliance:  $p < 0.05$  | The group achieved a non-significant lower than the usual thresholds - but still far from it at 0.408, resulting in null being not rejected In general, these results lead to the conclusion that Efficiency, Accuracy in fraud detection and compliance do not impact professional role significantly according to this examination.

## VI. DISCUSSION

The absence of such outcomes in the study suggests essential insights on where the AI and ML integration within financial reporting and auditing contexts currently stands. This hints that the real-world application and perception of these technologies might fall behind what theoretical and controlled experimental results suggest, perhaps reflecting an implementation lag or cultural resistance (or extended training/adaptation period). The results underline the need for future research to take a deeper look into these moderating factors that affect

financial and auditing services, as they contribute toward the complexity of technological integration with such highly-specialized professional tasks while also imposing significant barriers towards fully realizing AI/ML's impact on redefining current professions involved.

The results of the analysis found non-significant associations between AI and ML perceptions on role-related efficiency ( $p = 0.587$ ). This is in stark contrast to concurrent research - as per the Jan (2021) paper above or more broadly, dozens of papers that point towards machine learning systems revolutionizing accounting work by making dull rote activity even easier / faster; doing so should hold accountants have at least some additional time on their hands which they ought be spending pushing up into value add activities. It could suggest the findings that automation is automating tasks, but not (yet) perceived to be shifting roles in a way where employees are feeling any real meaningful impact. It could also indicate that other factors like how and when organizations are implementing these reforms, or compliance within the firm is moderating this effect (Ali et al., 2022).

Similarly the analysis showed that there was no statistically significant impact of AI/ML on accuracy perceptions to professional roles ( $p = 0.562$ ) This result is consistent with Kaur and Nasir (2020) who found varied benefits of AI in regard to accuracy stating that whilst there may be improved

computational accuracy, the complexity of decisions in uncertain contexts can remain an issue. We found evidence that professionals may not have the trust or perceive improvements in accuracy of these AI, ML techniques possibly due to worries about algorithmic transparency or maybe because it is early days yet in this technology lifecycle.

Results from the study also demonstrates no perceived affect of AI/ML on job function by fraud detection capabilities ( $p = 0.843$ ). This is contrary to available evidence such as that of Sharma and Panigrahi (2018), who suggested significant improvements in fraud detection via AI enabled systems considerably. This difference may be due to the particular context of the sample, or alternatively perhaps a lack in depth and breadth experience with AI capabilities inside organisations across the samples (Fedyk et al., 2022). No major impact of AI over perception regarding compliance in professional roles ( $p = 0.408$ ), outcome is presented This is in accordance with the results observed by Thompson et al. (2021), volunteering that although AI systems can assist with compliance, they frequently do so only in an indirect manner and against the backdrop of substantial existing capabilities for ensuring regulatory adherence. This could also be indicative of a gap in regulatory evolution around AI, where we bear witness to the possible yet not quite fully realized potential (or accepted capacity) of new technologies in use (AI-Sayyed et al., 2021).

## VII. CONCLUSION

The study aimed to investigate the impact of artificial intelligence (AI) and machine learning (ML) on financial reporting and auditing activities professional roles. The expectations established by the incumbent literature and rhetoric in use are that AI & ML could boost various dimensions of professional work to great extent, such as increase operations works efficiency; enhance accurate financial data income; upgrade fraud detection capabilities and deliver improved habitual standard compliance. Meanwhile, the experience of 142 accountants within Erbil private business firms data showed that AI and ML technologies did not appear to have a significant effect on these main professional components. This absence of perceived impact is important because it suggests that the transformational capabilities of AI and ML often considered to benefit financial accounting and auditing are not realised in practice. Such discrepancy promote consideration on the actual utilisation and efficacy of these technologies in real-world perhaps because they are not as rosy, as one used to see it from media/academic projection.

These results suggest the need for a more granular understanding of AI and ML adoption and use in practice. As such, it seems that there may be more nuance and complexity involved in the successful introduction of these technologies into workplace. The nature of the impact exerted by AI and ML could be affected considerably depending on such factors as whether it is a qualified routine job, how prepared the organization to uptake new technologies if they do so swiftly enough that these workers will still remain in employment with them and adapt further or retrain plus what sort of financial tasks are involved. Additionally, these results shed light on how AI and ML are being presented to professionals at large as well. Theoretical capabilities of these technologies and practical applicability / relevance to everyday professional tasks Specific in environments that may not have infrastructure or organizational culture needed for full implementation with more advanced technology.

## VIII. RECOMMENDATIONS

Based on the findings, the study recommended:

1. Enhanced Training and Education: Organizations should invest in comprehensive training programs to help professionals understand and effectively utilize AI and ML tools. This could bridge the gap between technology availability and its practical use.
2. Incremental Implementation: Instead of large-scale overhauls, companies could implement AI and ML technologies incrementally, allowing time for adjustment and acceptance among professionals.
3. Transparency and Governance: Develop clear guidelines and governance structures around AI and ML use, which could help in building trust among professionals regarding the accuracy and ethical use of these technologies.

### Practical Implications

The study highlights the importance of considering human factors and organizational culture when introducing AI and ML into traditional practices. The lack of significant impact suggests that merely adopting new technologies is not enough; businesses must also foster an environment where these tools are effectively integrated into daily workflows.

### Future Studies

Future research should focus on:

- Qualitative Insights: Qualitative studies could provide deeper insights into why AI and ML are not perceived as significantly impacting professional roles.
- Cross-Industry Comparison: Comparing how AI and ML impact different industries may reveal factors that

facilitate or hinder the effective adoption of these technologies.

- Longitudinal Studies: Long-term studies could track changes over time as professionals and organizations become more accustomed to AI and ML.

### Research Limitations

This study's limitations include:

- Geographical Limitation: The study was confined to accountants in Erbil, which might not represent broader global trends.
- Sample Size: While statistically adequate, a larger sample size could provide more granular insights into different subgroups' perceptions.

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