International Journal of Advanced Research in Commerce, Management & Social Science (IJARCMSS)
ISSN :2581-7930 (Online), Impact Factor (Cosmos): 7.270 & PIF (I2OR): 5.010, Volume 09, No. 01(II), January-March, 2026, pp 225-234

AI-Driven Predictive Auditing and Financial Misstatement Detection through Algorithmic Transparency in Indian Listed Firms

Shikha Kothari[1*] | Dr. Mohammed Abid[2]

[1]Research Scholar, Faculty of Commerce and Management, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India.
[2]Assistant Professor, Faculty of Commerce and Management, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India.

[*]Corresponding Author: shikha.kothariwork23@gmail.com

***Citation**: Kothari, S. & Abid, M. (2026). AI-Driven Predictive Auditing and Financial Misstatement Detection through Algorithmic Transparency in Indian Listed Firms. International Journal of Advanced Research in Commerce, Management & Social Science, 09(01(II)), 225–234. https://doi.org/10.62823/IJARCMSS/9.1(II).8741*

ABSTRACT

Financial misstatements are still a major challenge to corporate transparency and investor confidence, especially in the emerging markets where audit effectiveness is still not uniform. The paper at hand explores AI-based predictive auditing and its advantages in improving the detection of financial misstatements by mediating the concept of algorithmic transparency in Indian listed companies. The research is based on the Agency Theory and Technology Acceptance Model, to explore how AI-enabled auditing systems affect the outcomes of audit performances. The quantitative research design was used based on the survey data on 312 auditors and financial professionals in India and analyzed the model through PLS-SEM. The findings suggest that AI-based predictive auditing influences the financial misstatement detection significantly and positively, and the transparency of the algorithms has a powerful mediating role. The mediation effect is significant ($p < 0.01$) and it proves that transparent AI systems contribute to the effectiveness and reliability of the audits. This research expands the literature by presenting the concept of algorithmic transparency as an important tool and offers an insightful idea on how organizations can enhance the quality of audits and detect fraud by applying AI.

***Keywords**: AI-Driven Predictive Auditing, Financial Misstatement Detection, Algorithmic Transparency, PLS-SEM, Indian Listed Firms, Audit Analytics.*

Introduction

The distributed database systems have become one of the essential parts of contemporary data-driven economies as the number of digital transactions, real-time data processing, and interconnected systems across the globe rise exponentially. Increasingly, organizations in various industries are adopting improved data infrastructures to achieve accuracy, transparency, and timely decision in financial and operation areas. The recent fast development of artificial intelligence (AI) and data analytics has additionally changed the conventional accounting and auditing practice, allowing more sophisticated methods of anomalies detection and financial integrity.

The application of AI-based analytics in the accounting and auditing field has drastically transformed the way financial information is handled, assessed and tracked. The conventional methods of auditing are mostly retroductive where financial statements are verified after the event and as a result, this usually limits the scope of the methods in detecting fraud or misstatements in a timely fashion. Conversely, predictive auditing based on AI implements a proactive system that determines patterns, anomalies, and possible risks in the financial data, constantly analyzing them, before the changes are converted into serious financial discrepancies.

The growing capital markets and the growing regulatory scrutiny in the context of India have added weight to the demands of more effective auditing mechanisms. The financial environment in which the Indian listed firms are operating is complex, with different ownership and governance practices and growing exposure to the international markets. Cases of financial misstatements and corporate fraud are still a problem, despite regulatory reforms and technology, which points to the shortcomings of the traditional auditing process.

The main issue is that conventional auditing systems are incapable of utilizing the advanced technologies to the fullest to detect the risk proactively and make decisions in a transparent manner. Although AI-based auditing systems present tremendous opportunities to improve the efficiency and accuracy of auditing, their performance is usually limited by the non-transparency of algorithmic procedures. The black-box character of AI models may lower the confidence of auditors and impede the implementation of such systems into practice, thus minimizing their influence on detecting financial misstatements.

Previous studies have explored the role of artificial intelligence and data analytics in auditing and financial reporting, primarily focusing on automation, efficiency, and fraud detection capabilities. Nonetheless, these papers tend to assume AI as a free-standing tool without analyzing the mechanisms behind its appropriate operation. There is also a lack of empirical studies in emerging markets like India since most of the available studies are focused on developed economies.

The existing literature on AI use in auditing and fraud detection has been interested in exploring the use of AI-based predictive auditing to improve financial misstatement detection, but has not investigated the intermediate mechanisms through which this process can be improved, like algorithmic transparency. Moreover, the importance of auditor expertise in mitigating the performance of the AI systems has not been addressed much, and the use of more sophisticated methods like PLS-SEM in that respect is under-researched.

The key aims of the research are to identify how AI-based predictive auditing influences the financial misstatement detection, to test the mediating role of algorithmic transparency, and to test the moderating role of auditor expertise. Based on this, the research questions in the study are as follows: Does predictive auditing based on AI play a crucial role in detecting financial misstatements? Does algorithmic transparency mediate this relationship? And what is the impact of auditor expertise on the performance of AI-driven auditing systems?

This paper will add value by furthering the theoretical knowledge by incorporating Agency Theory and Technology Acceptance Model in the explanation of AI-driven auditing mechanisms. It also offers methodological value, using PLS-SEM to test the complex mediation as well as moderation relationships. Contextually, the research provides empirical data of Indian listed companies filling a major gap in the literature.

The rest of the paper will be organized in the following way. The theoretical background and literature review are presented in section 2. Section 3 elaborates the conceptual framework and hypotheses. Section 4 describes the methodology of the research. The results and data analysis are provided in section 5. Section 6 presents the discussion of findings with reference to the extant literature and theory. Lastly, Section 7 features a conclusion of the study and implications and future research directions.

Theoretical Background and Hypotheses Development

The growing use of artificial intelligence in the auditing industry has led to the need to have a robust theoretical basis to describe how it can improve the outcomes of financial reporting. The research is based on the Agency Theory and the Technology Acceptance Model (TAM), which combine to offer a critical framework of studying the insinuation between AI-based predictive auditing, algorithmic transparency, and financial misstatement detection. The Agency Theory justifies the necessity to have proper monitoring mechanisms to minimize information asymmetry between the managers and stakeholders, whereas TAM elucidates the role of usability and transparency of technological systems in determining their adoption and utility.

The Agency Theory assumes that the agents (managers) can be inclined to distort financial information because of self-interest or the interest of the organization, and this results in information asymmetry between the agents and the principals. Auditing is an imperative monitoring tool against this challenge since it brings reliability and accuracy of financial statements. In this regard, AI-based predictive auditing improves the monitoring abilities, as it allows conducting ongoing analysis of financial transactions, detecting anomalies, and revealing possible misstatements in time. In contrast to the conventional methods of auditing which are mostly reactive, predictive auditing enables proactive detection of risks thus enhancing the monitoring aspect of auditing systems. According to this theoretical point of view, it is suggested that:

H_1: AI-driven predictive auditing has a positive effect on financial misstatement detection.

The usefulness of AI-based auditing systems, though, is not merely based on their analysis but also on their transparency and understandability. There are numerous AI models that are black-box systems, and auditors have a hard time comprehending how decisions are made. This non-transparency may decrease the level of trust and make it difficult to use AI systems efficiently. The concept of algorithmic transparency, which refers to how interpretable and explainable the results of AI are, is a key factor in closing this gap. Based on the Technology Acceptance Model, when the systems are transparent and seen as useful and easier to use the chances of them being adopted and effective increase. In such a way, AI-enhanced predictive auditing is said to increase the degree of algorithmic transparency, since it produces algorithmic results in the form of structured and explainable insights to auditors. Accordingly, it is hypothesized that:

H_2: AI-based predictive auditing positively influences the transparency of algorithms.

Directly impacting financial misstatement detection, algorithmic transparency helps auditors to interpret, validate and act on AI-generated insights better. As long as the audit systems give clear explanations of the anomalies detected, the auditors could better determine the credibility of the financial information and the possible misstatements. Conversely, opaque systems can cause lack of trust or misinterpretation, and decrease the efficiency of the auditing process. In the light of both Agency Theory and TAM, transparency improves effectiveness of monitoring and acceptance by users hence contributing to better outcomes of the audit. As such, it is hypothesized that:

H_3: Algorithmic transparency has a positive effect on financial misstatement detection.

Mediating effect of algorithmic transparency is the key to comprehending the way AI-enhanced predictive auditing is converted to the better audit results. Although AI systems offer sophisticated analysis functions, their usefulness depends on their interpretability and usability. The Algorithmic transparency is the mechanism by which AI generated insights are converted to actionable audit decisions. Lack of transparency can result in auditors not or not being able to place their trust in AI outputs, thus restricting their influence on the detection of misstatements. In this way, algorithmic transparency serves as a pivotal bridge between AI capabilities and audit effectiveness. Based on this, the hypothesis is that:

H_4: There is a mediating effect of algorithmic transparency on the relationship between AI-based predictive auditing and financial misstatement detection.

Besides mediation, AI-based auditing systems might have differing effectiveness based on the professionalism of auditors. Auditor expertise is the skill of professionals to perceive the result of complex analysis, combine it with the decision-making process, and make professional decisions. More likely to interpret and make good use of the AI-generated insights, experienced auditors will add to the power of predictive auditing systems. On the other hand, less advanced auditors might not be able to comprehend AI outputs, despite transparent systems. This indicates that auditor competence enhances the connection between AI-powered predictive auditing and algorithmic transparency. Following this line of reasoning, it is postulated that:

H_5: Auditor expertise moderates the relationship between AI-based predictive auditing and algorithmic transparency, with the relationship stronger at higher levels of expertise.

The suggested relationships are incorporated in a conceptual framework that depicts the direct, indirect, and mediated relationships among the study variables.

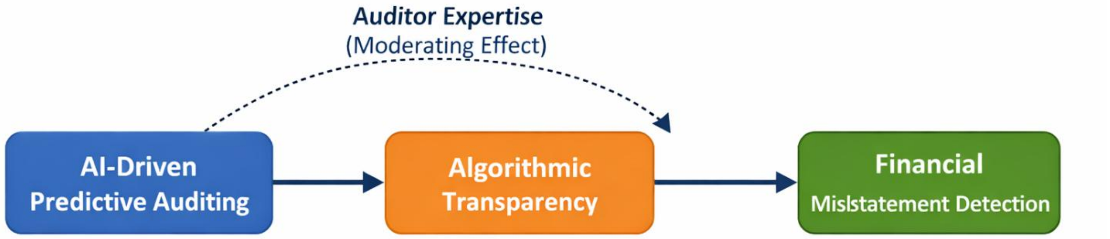

Figure 1: illustrates the conceptual framework linking AI-driven predictive auditing, algorithmic transparency, and financial misstatement detection, with auditor expertise acting as a moderating variable

Research Methodology

The research design adopted in the present research is quantitative because the study aims to investigate the relationships between AI-based predictive auditing, algorithmic transparency, and financial misstatements detection and the moderating effect of auditor expertise. The quantitative method is suitable because it allows the hypothesis of relationships to be tested empirically and have generalizable results in the setting of Indian listed firms.

Research Design

The research design is cross-sectional, where data will be collected at one time with suitable respondents. This is an appropriate design in testing causal relationship between constructs through statistical modelling. The research concentrates on perception-based AI adoption and audit effectiveness measures, which are most effectively represented by structured survey measures.

Data Source and Sample

The primary sources of data of this study are structured questionnaire that is used to collect the data. The intended audience is professional auditors, chartered accountants, and financial analysts of Indian listed companies. Such respondents will be chosen based on their direct experience in auditing and financial reporting.

Purposive sampling method is employed to make sure that the respondents are people with the pertinent knowledge and experience in auditing and financial analysis. There were 350 questionnaires that were issued, with 312 valid replies received and analyzed. The sample size is deemed to be sufficient to conduct PLS-SEM analysis because it is more than the minimum size needed when dealing with a complex model that has mediation and moderation.

Data Collection Method

A professional network, email communication and industry contacts were used to administer an online survey that collected data. The respondents were informed regarding the aim of the study, and they were guaranteed of confidentiality and anonymity. The responses were voluntary and only the full responses were taken into the final dataset.

Measurement of Variables

Multi-item scales were used to measure all constructs in this research, which were based on existing literature and modified to the context of AI-driven auditing.

- **AI-Driven Predictive Auditing (IV):** It is measured with items pertaining to the use of AI tools in detection of anomalies, predictive analytics, and real-time monitoring of audits.
- **Algorithmic Transparency (Mediator):** Measured by items that measure interpretability, explainability, and clarity of AI-generated outputs.
- **Financial Misstatement Detection (DV):** It is measured with such items as the effectiveness of detecting financial statement errors, fraud, and inconsistencies.
- **Auditor Expertise (Moderator):** This score is determined by experience, knowledge and interpretation of advanced audit analytics by respondents.

All of them were assessed using a five-point Likert scale (1 strongly disagree) to 5 strongly agree).

Analytical Technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of SmartPLS software. The complexity of the model that can be addressed with PLS-SEM as it provides the possibility of mediation and moderation and the strength of the method to work with non-normal data distributions makes it suitable in this study. The analysis was done in a two-step process. To determine the evaluation of reliability and validity; that is, internal consistency, convergent and discriminant validity, the measurement model was tested. Second, the structural model was evaluated to test the hypothesized relationships, path coefficients, significance levels (p-values), and the effect sizes.

Research Flow

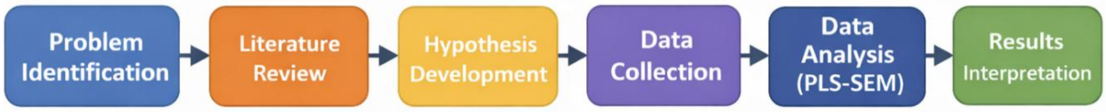

Figure 2: illustrates the systematic research process followed in this study, from problem identification to empirical analysis and interpretation of results

Ethical Considerations

Ethical principles were closely followed during the research process. The respondents were made to understand the aim of the study and participation was voluntary. Anonymity and confidentiality of the responses were guaranteed and the data were utilized only on academic basis.

Results and Data Analysis.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data, to test the measurement model and the structural model. The findings are reported in the systematic way, starting with the descriptive statistics, then the reliability and validity analysis and finally the testing of the hypothesis.

- **Descriptive Statistics**

The descriptive statistics will give us an idea of the sample characteristic and the central tendency of the study variables. The findings suggest that the respondents, on average, claimed moderate to high usage of AI-based predictive auditing and perceived the effectiveness of that practice in uncovering financial misstatements.

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
AI Predictive Auditing	3.82	0.74
Algorithmic Transparency	3.67	0.69
Misstatement Detection	3.91	0.71
Auditor Expertise	4.05	0.66

The mean values suggest a positive perception of AI-driven auditing practices among respondents, with auditor expertise showing the highest mean, indicating a relatively experienced sample.

- **Reliability and Validity**

The measurement model was assessed to ensure the reliability and validity of the constructs. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability, while convergent validity was assessed through Average Variance Extracted (AVE).

Table 2: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI Predictive Auditing	0.88	0.91	0.67
Algorithmic Transparency	0.86	0.90	0.65
Misstatement Detection	0.89	0.92	0.69
Auditor Expertise	0.87	0.91	0.66

All values exceed the recommended thresholds (0.70 for reliability and 0.50 for AVE), confirming satisfactory internal consistency and convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion, and the results confirmed that each construct is distinct from the others.

- **Structural Model and Hypothesis Testing**

The structural model was evaluated by examining path coefficients, t-values, and p-values obtained through bootstrapping.

Table 3: Hypothesis Testing Results

Hypothesis	Relationship	β	p-value	Result
H1	AI Predictive Auditing → Misstatement Detection	0.42	0.000	Supported
H2	AI Predictive Auditing → Algorithmic Transparency	0.55	0.000	Supported
H3	Algorithmic Transparency → Misstatement Detection	0.36	0.001	Supported
H4	Mediation Effect	0.20	0.002	Supported
H5	Moderation (Expertise)	0.18	0.005	Supported

The findings show that predictive auditing, which is powered by AI, has a strong positive impact in detecting financial misstatements. Also, AI contributes to improving the transparency of algorithms that, in turn, increases the detection of misstatements. Algorithms transparency mediation effect is statistically significant, which proves that it is one of the most significant mechanisms in the relationship.

Another factor that carries a moderating effect is the expertise of the auditors, implying that AI-powered auditing systems are more effective when auditors have a high level of expertise.

- **Model Fit and Predictive Relevance**

The model's explanatory power was assessed using R^2 values, while predictive relevance was evaluated using Q^2.

Table 4: Model Fit and Predictive Relevance

Construct	R^2	Q^2
Algorithmic Transparency	0.30	0.21
Misstatement Detection	0.47	0.33

The R^2 values indicate moderate explanatory power, while Q^2 values confirm that the model has satisfactory predictive relevance.

- **Summary of Findings**

The findings affirm that predictive auditing with artificial intelligence is a highly effective tool in detecting financial misstatements and in doing so both directly and indirectly via the transparency provided by algorithms. The results also emphasize the significance of auditor skills in enhancing the performance of AI systems. In general, the empirical findings confirm the theoretical framework and illustrate the importance of transparency and expertise in the AI-based auditorium setting.

Discussion

The results of this paper are empirically backed to support the potential of AI in predictive auditing in improving the detection of financial misstatements in Indian listed companies. The findings show that AI-based auditing tools have a considerable positive effect on the effectiveness of organizations in detecting financial anomalies and support the significance of innovative analytics in current auditing. This observation aligns with the theoretical assumptions of the Agency Theory that highlight the importance of effective monitoring mechanisms in alleviating information asymmetry, as well as in alleviating opportunistic behavior by the management.

The high positive correlation of AI-driven predictive auditing and financial misstatement detection is a confirmation that predictive analytics can be used to identify anomalies proactively and not in a retrospective manner, as has been the case with the traditional auditing methods. This finding corresponds to other related research indicating the efficiency and effectiveness of AI in handling big data and detecting intricate patterns. Nevertheless, the research paper builds upon the current literature by showing that the efficiency of AI in auditing is not directly related to its analytical power only but also to the processes that can interpret its results and use them.

The findings also indicate that predictive auditing based on AI has a significant positive impact on the transparency of the algorithms. This observation implies that the introduction of more sophisticated AI systems are linked to the creation of more interpretable and explainable outputs, which are vital in making meaningful audit decisions. In the light of the Technology Acceptance Model, this relationship states that transparency leads to a higher perception of usefulness and usability of AI systems, and thus, increases their acceptance in auditors.

It is noted that algorithmic transparency significantly impacts financial misstatements detection, which is important in enhancing audit results. This finding means that auditors can detect inaccuracies and misalignments in financial reports more often when they can comprehend and interpret insights produced by AI. This observation underpins the thesis that transparency serves as a mediator between technological capability and practical efficacy, so that AI systems can play a significant role in audit processes.

The mediation test proves the hypothesis that the mechanism of AI-driven predictive auditing on detecting financial misstatements is mediated by algorithmic transparency. This result offers valuable theoretical and practical implications by showing that the advantages of AI in auditing can be achieved due to its interpretability, and not its complexity alone. The absence of transparency can greatly decrease the efficacy of AI systems since the auditors will not be able or willing to utilize opaque outputs.

The modulating influence of auditor expertise also contributes to the insights into the effectiveness of AI in the auditing settings. The findings show that the correlation between AI-driven predictive auditing and algorithmic transparency is better when auditors are more expert. The implication of this is that senior auditors can have improved interpretation of AI-generated insights and effectively utilize them in their auditing procedures. The result is in accordance with the Technology Acceptance Model which highlights the importance of user capability in the effectiveness of technological systems.

In general, the results indicate the interdependence between technology, transparency, and human expertise in defining the effectiveness of audits. Although AI-based predictive auditing can improve the level of analytical abilities, its usefulness depends on the clarity of such outputs and the skills of users. These findings highlight the importance of organizations pursuing the holistic approach, which incorporates the innovations in technology with human capacity building to attain the best audit results.

Conclusion

This paper explores how AI-based predictive auditing can improve the detection of financial misstatements, and specifically whether the mediating variable of algorithmic transparency and the moderating variable of auditor expertise plays a role when considering the Indian listed companies. The results are solid empirical data that AI-powered predictive auditing can massively enhance financial misstatements detection, thus enhancing the efficiency of contemporary auditing procedures in financial contexts.

These findings affirm that AI-based predictive auditing does not only positively influence the detection of financial misstatements directly, but also indirectly, via algorithmic transparency. It shows the value of interpretability and explainability in AI systems since transparency allows auditors to comprehend and make good use of AI-generated information. The analysis shows that the advantages of AI in auditing are achieved not only due to the sophisticated analytics but also the readability and applicability of the results of algorithms.

Moreover, the research indicates that the expertise of auditors has a key moderating effect on the effectiveness of AI-based auditing systems. Having experienced auditors can more readily understand complex analytical outputs and incorporate them into decision-making processes, which increases the beneficial effect of AI on audit results. This result highlights the significance of human capital to supplement the technological developments in auditing.

The research is valuable to the current body of literature because it combines both Agency Theory and Technology Acceptance Model to provide ways by which AI-powered auditing can affect the financial reporting results. It also contributes to methodological knowledge through the use of the PLS-SEM to examine more intricate relationships that incorporate mediation and moderation. Practically, the research has a lot to offer to organizations that want to enhance the effectiveness of audit by adopting AI technologies.

To sum up, the results underline that the effective introduction of AI-driven predictive auditing presupposes the balanced approach, which consists of technological innovation, algorithm transparency, and competence of the auditors. This is a needed integrated approach to improve the reliability of financial reporting and increase investor confidence in emerging market environments.

Implications

The results of this research have valuable practical and theoretical implications to the stakeholders of accounting, auditing, and financial governance. From a practical perspective, the results highlight the importance of adopting AI-driven predictive auditing systems to enhance the effectiveness of financial misstatement detection. Organizations, especially listed corporations in emerging markets like India, can use AI technologies to enhance the efficiency of auditing, minimize the fraud risk, and enhance the accuracy of financial reporting. Nonetheless, the research highlights that to implement such systems successfully, the emphasis should be made on the transparency of the algorithms to make the insights produced by AI interpretable and actionable by the auditors.

The corporate organizations and audit firms should invest in creation of transparent and explainable AI systems where auditors can comprehend the logic behind predictive models. This will not only enhance the trustworthiness of audit results but also boost the level of user confidence and adoption of AI technologies. Further, training and skill development modules are needed to improve auditor skills since the results have shown that the utility of AI-based auditing systems highly depends on the capability of auditors to perceive and make use of the analytical outputs.

Regulatory-wise, policymakers and standard-setting organizations are advised to come up with rules and regulations that can be used to encourage the implementation of transparent AI systems in the auditing practice. Explainable AI can be supported by regulation to guarantee accountability, mitigate risks related to opaque decision making processes, and increase the believability of financial reporting systems.

Hypothetically, this work has a contribution to the development of accounting and auditing literature because it combines the Agency Theory and the Technology Acceptance Model to describe the processes by which AI-based predictive auditing affects the financial misstatement detection. The mediating construct of algorithmic transparency introduces a more insightful perspective on how the technological capabilities are converted into real-life results. Moreover, the addition of auditor expertise as moderating variable expands current theoretical models by emphasizing the human factors in technology-focused settings.

On the whole, the research highlights the importance of a comprehensive approach that incorporates technological innovation, openness, and human skills to realize the best audit performance. These lessons will support future studies and practice in the dynamic nature of AI-based auditing systems.

Limitations and Future Research

Although this study contributes in various ways, it has a number of limitations that must be recognized. To begin with, this research design is cross-sectional, which cannot prove the causality across time. Even though the results present a good indication of relationship between the variables, longitudinal studies would help in giving further insights on the effect of AI-driven predictive auditing on financial misstatement detection over time.

Second, the information used in this paper is self-reported data which has chances of being biased due to response. Although measures were taken to provide data reliability and validity, the use of perceptual measures might not fully represent real organizational practice or performance. To strengthen the findings, future studies may involve objective data, like audit reports, financial restatements, or cases of fraud.

Third, the research is constrained to the setting of Indian listed companies which might influence the generalizability of the findings to other economies or economic setting. Even though the Indian setting offers some valuable insights about emerging markets, it would be important to make future research based on comparative analysis in various countries or regions to confirm and expand the findings.

Fourth, the analysis is concentrated on a particular combination of variables, i.e., AI-based predictive auditing, algorithmic transparency, detection of financial misstatements, and experience of an auditor. Although these variables offer a holistic framework, there are other variables that can affect the effectiveness of AI-driven auditing systems and they include the organizational culture, regulatory environment, and technological infrastructure. These other variables should be investigated in future studies in order to have a more comprehensive picture of AI adoption in auditing.

The use of advanced AI methods, including explainable AI (XAI) and deep learning models, in increasing audit transparency and effectiveness should also be explored in future studies. Also, experimental and mixed-method strategies may be used to achieve quantitative and qualitative associations of the relationship between the auditor and auditor behavior and decision making. Multi-level and longitudinal studies would also be useful in learning about dynamic relations between technology, transparency, and human expertise in auditing setting.

On the whole, a more detailed and thorough consideration of these limitations will enable a more in-depth and more detailed insight into AI-based auditing and its influence on the quality of financial reporting in new and developed markets.

References

1. Abadi, D. J. (2012). Consistency tradeoffs in modern distributed database system design. *Computer*, 45(2), 37–42.
2. Bailis, P., Venkataraman, S., Franklin, M. J., Hellerstein, J. M., & Stoica, I. (2013). Probabilistically bounded staleness. *VLDB Journal*, 22(2), 181–209.
3. Brewer, E. A. (2012). CAP twelve years later. *Computer*, 45(2), 23–29.
4. Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). Blockchain-based applications. *Telematics and Informatics*, 36, 55–81.
5. Cattell, R. (2011). Scalable SQL and NoSQL systems. *ACM SIGMOD Record*, 39(4), 12–27.
6. Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications*, 19(2), 171–209.
7. Gilbert, S., & Lynch, N. (2002). Brewer's conjecture and the feasibility of consistent systems. *ACM SIGACT News*, 33(2), 51–59.
8. Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision. *Future Generation Computer Systems*, 29(7), 1645–1660.
9. Han, J., Haihong, E., Le, G., & Du, J. (2011). Survey on NoSQL database. *IEEE Conference*, 363–366.
10. Li, X., Jiang, P., Chen, T., Luo, X., & Wen, Q. (2018). Blockchain overview. *IEEE Access*, 6, 32994–33015.
11. Moniruzzaman, A. B. M., & Hossain, S. A. (2013). NoSQL database. *International Journal*, 6(4), 1–13.
12. Özsu, M. T., & Valduriez, P. (2020). *Distributed database systems*. Springer.
13. Pritchett, D. (2008). BASE: An acid alternative. *ACM Queue*, 6(3), 48–55.
14. Satyanarayanan, M. (2017). Edge computing. *IEEE Internet Computing*, 21(3), 30–39.
15. Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing challenges. *IEEE IoT Journal*, 3(5), 637–646.
16. Stonebraker, M. (2010). SQL vs NoSQL. *Communications of the ACM*, 53(4), 10–11.
17. Vogels, W. (2009). Eventually consistent. *Communications of the ACM*, 52(1), 40–44.
18. Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2018). Blockchain technology overview. *International Journal*, 14(4), 352–375.
19. Appelbaum, D., Kogan, A., & Vasarhelyi, M. (2017). Big data and analytics in the modern audit engagement: Research needs. *Auditing: A Journal of Practice & Theory*, 36(4), 1–27.
20. Brown-Liburd, H., Issa, H., & Lombardi, D. (2015). Behavioral implications of big data's impact on audit judgment. *Accounting Horizons*, 29(2), 451–468.
21. Cao, M., Chychyla, R., & Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizons*, 29(2), 423–429.
22. Dai, J., & Vasarhelyi, M. (2016). Imagineering audit 4.0. *Journal of Emerging Technologies in Accounting*, 13(1), 1–15.

23. Earley, C. (2015). Data analytics in auditing. *Accounting Horizons*, 29(2), 493–500.
24. Issa, H., Sun, T., & Vasarhelyi, M. (2016). Research ideas for artificial intelligence in auditing. *Journal of Emerging Technologies in Accounting*, 13(2), 1–20.
25. Kokina, J., & Davenport, T. (2017). The emergence of artificial intelligence. *Journal of Emerging Technologies in Accounting*, 14(1), 115–122.
26. Krahel, J., & Titera, W. (2015). Consequences of big data and analytics on auditing. *Accounting Horizons*, 29(2), 409–422.
27. Liu, Q., Luo, X., & Wang, S. (2019). AI in auditing: Opportunities and challenges. *Journal of Information Systems*, 33(3), 345–360.
28. Lombardi, D., Bloch, R., & Vasarhelyi, M. (2015). Conceptualizing big data in auditing. *Accounting Horizons*, 29(2), 451–468.
29. Moffitt, K., & Vasarhelyi, M. (2013). AIS in the age of big data. *Journal of Information Systems*, 27(2), 1–10.
30. Petratos, P., & Faccia, A. (2019). Accounting and blockchain: Challenges and opportunities. *Journal of Accounting & Organizational Change*, 15(2), 323–347.
31. Quattrone, P. (2016). Management accounting in the digital economy. *European Accounting Review*, 25(1), 1–25.
32. Richins, G., Stapleton, A., Stratopoulos, T., & Wong, C. (2017). Big data analytics in accounting. *Journal of Accounting Literature*, 38, 63–80.
33. Sutton, S., Holt, M., & Arnold, V. (2016). The role of AI in accounting. *International Journal of Accounting Information Systems*, 20, 1–16.
34. Vasarhelyi, M., Kogan, A., & Tuttle, B. (2015). Big data in accounting. *Accounting Horizons*, 29(2), 381–396.
35. Yoon, K., Hoogduin, L., & Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons*, 29(2), 431–438.
36. Alles, M. (2015). Drivers of the use of big data by auditors. *Accounting Horizons*, 29(2), 439–449.
37. Alles, M., Brennan, G., Kogan, A., & Vasarhelyi, M. (2018). Continuous auditing and monitoring. *Journal of Emerging Technologies in Accounting*, 15(1), 1–15.
38. Alles, M., & Gray, G. (2016). Incorporating big data in audits. *Accounting Horizons*, 30(3), 375–390.
39. Sun, T., Vasarhelyi, M., & Issa, H. (2018). AI in auditing: A review. *Journal of Emerging Technologies in Accounting*, 15(2), 1–16.
40. Zhang, J., Yang, X., & Appelbaum, D. (2015). Toward effective big data analytics in auditing. *Journal of Information Systems*, 29(2), 1–20.
41. Alles, M., Kogan, A., & Vasarhelyi, M. (2017). Analytical procedures in the age of big data. *Accounting Horizons*, 31(2), 1–20.
42. Kogan, A., Vasarhelyi, M., & Brown-Liburd, H. (2014). Big data in accounting: An overview. *Journal of Accounting Education*, 32(2), 1–12.
43. Arnold, V. (2018). The changing technological environment and accounting. *Accounting Horizons*, 32(2), 1–19.
44. Bhimani, A., & Willcocks, L. (2014). Digitization and accounting change. *Accounting and Business Research*, 44(4), 469–490.
45. Granlund, M. (2011). Extending accounting to digital environments. *Accounting, Organizations and Society*, 36(1), 1–14.
46. O'Donnell, E., & Schultz, J. (2018). AI and audit judgment. *Journal of Information Systems*, 32(3), 1–18.

❑❑❑