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The Role of Statistical Concepts in the Development of Artificial Intelligence for Auditing: A Systematic Literature Review

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Abstract

Artificial Intelligence (AI) has increasingly been adopted in auditing, however the role of statistical methods in improving AI performance and reliability remains fragmented. This study aims to systematically identify, review, and synthesize the role of statistical concepts in AI development for auditing, including their implementation, benefits, challenges, and future directions. A Systematic Literature Review (SLR) following the PRISMA framework was conducted on 149 studies published between 2017 and 2026 from Google Scholar, Scopus, and SciSpace. The findings reveal a significant increase in AI auditing research since 2023. Regression analysis, hypothesis testing, and Bayesian inference are the most frequently applied statistical methods, supporting fraud detection, risk assessment, audit sampling, anomaly detection, and model validation. Integrating statistical methods with AI improves prediction accuracy, interpretability, transparency, and audit quality. However, challenges remain regarding data quality, model interpretability, auditor competency, and AI governance. Future research should prioritize hybrid AI-statistical models, Explainable AI, and adaptive Bayesian approaches to enhance trustworthy data-driven auditing

Keywords Artificial Intelligence; Statistical Methods; Auditing; Explainable AI; Systematic Literature Review

INTRODUCTION

The development of Artificial Intelligence (AI), machine learning, and statistical methods has driven significant changes in modern audit practices. The increasing complexity of business transactions, the increasing volume of financial data, and the need for more accurate and efficient audit processes have made AI-based technology a primary focus of research in the audit field (Celestin, 2024; Giri et al., 2025a). In recent years, audit approaches have shifted from manual sampling techniques to data-driven approaches that integrate predictive analytics, machine learning, statistical models, and Explainable Artificial Intelligence (XAI). This transformation enables continuous risk assessment, automated anomaly detection, and real-time audit monitoring (Celestin & Vanitha, 2019; Chen et al., 2025; Giri et al., 2025a).

Various empirical studies have shown that the application of AI in auditing can significantly improve the effectiveness of the audit process. AI-based audit systems have been reported to increase fraud detection accuracy from approximately 65% to over 90%, while reducing audit duration and costs (Celestin, 2024; Zhao, 2025). Other studies have also shown an increase in fraud detection accuracy of approximately 35% and a reduction in audit completion time of up to 40%, thereby strengthening financial reporting transparency, internal control effectiveness, and regulatory compliance (Celestin & Vanitha, 2019; Celestin, 2024).

However, the implementation of AI and statistical methods in auditing still faces various challenges. The integration of statistical models, such as regression analysis, hypothesis testing, and Bayesian inference, with AI algorithms has not yet fully produced an optimal framework to support risk assessment and audit decision-making (Derks et al., 2022; Toraldo & Priuli, 2022). Furthermore, conventional audit processes, which still rely on manual sampling, are often ineffective in handling large amounts of data, potentially leading to delays in anomaly and fraud detection (Celestin, 2025).

The research gap is also evident in the lack of models capable of integrating statistical and AI methods in a balanced manner to improve predictive accuracy while maintaining model interpretability. Issues such as algorithm transparency, data quality, privacy protection, and the balance between automation and auditor professional judgment remain hotly debated (Bhaumik & Dey, 2023; Giudici et al., 2024; Chen et al., 2025; Dash et al., 2025; Imane, 2025). If these challenges are not addressed, audit quality could decline, the risk of undetected fraud could increase, and stakeholder confidence in audit results could be undermined (Antwi et al., 2024).

Based on these conditions, this literature review is built on a conceptual framework that integrates statistical methods, machine learning, and AI in the audit process. Statistical models function to establish relationships between variables, test hypotheses, and validate analysis results, while machine learning supports automatic pattern identification and anomaly detection. On the other hand, Explainable Artificial Intelligence (XAI) plays a role in increasing transparency and accountability of decisions generated by AI models (Toraldo & Priuli, 2022; Giudici et al., 2024; Chen et al., 2025). The integration of these three approaches is expected to produce a more accurate, efficient, and easily interpretable audit system in accordance with applicable professional standards and regulations. This study aims to systematically identify, review, and synthesize research on the role of statistical concepts in the development of Artificial Intelligence for auditing, as well as analyze its implementation, benefits, challenges, and development directions in supporting data-driven audit processes.

METHODS

This study employed a qualitative approach using the Systematic Literature Review (SLR) method. A Systematic Literature Review is a method used to systematically collect, critically examine, and integrate various research findings relevant to a topic or research question (Norlita et al., 2023). The article selection process was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a systematic and transparent literature review. The literature collected in this study was sourced from scientific publications.

The initial search was conducted through the scientific databases Scopus, Google Scholar, and scispace, searching for articles relevant to the topic of statistics and Artificial Intelligence in auditing activities. The articles were then screened in stages, starting from reviewing the title and abstract, to reading the full text—with reference to the inclusion and exclusion criteria that had been set.

FINDINGS AND DISCUSSION

Publication Trends in AI and Statistical Methods for Auditing (2017–2026)

Based on the literature identification and selection process conducted using the Systematic Literature Review (SLR) approach following the PRISMA framework, a total of 149 relevant scientific publications focusing on the role of statistical methods in the development of artificial intelligence (AI) for auditing were identified. The literature search was performed using reputable academic databases, including Google Scholar, SciSpace, and Scopus, covering publications from 2017 to 2026. The annual distribution of publications reveals a gradual increase in research output over the observation period.

Empirically, the publication trend demonstrates three distinct phases in the evolution of the literature over the past decade. The first phase (2017–2022) represents the formative stage of technology-driven auditing research. During this period, the annual number of publications remained relatively low, with fewer than ten articles published each year. This limited research output suggests that AI adoption in auditing was still largely conceptual, while computational infrastructure and analytical capabilities within the accounting and auditing disciplines had not yet reached the level of maturity observed in fields such as manufacturing or the natural sciences. Research integrating statistical methodologies with AI emerged more consistently after 2020, although the growth trajectory remained relatively modest.

The second phase (2023–2025) was characterized by a substantial paradigm shift in the research landscape. Beginning in 2023, publication output increased dramatically and reached its highest level in 2025, with a total of 81 publications. This exponential growth coincided with the global emergence and commercialization of advanced generative artificial intelligence technologies. Most studies during this period focused exclusively on AI applications (n = 68), whereas research integrating AI with statistical methodologies also reached its highest level, accounting for 13 publications in 2025. This trend reflects an increasing academic recognition of the necessity to validate AI algorithms using rigorous statistical frameworks in order to minimize algorithmic bias, reduce hallucination risks, and enhance the reliability of AI-based fraud detection systems.

The third phase (2026) shows a decline in the number of publications. However, this decrease should not be interpreted as a reduction in scholarly interest in AI applications for auditing. Rather, the 2026 data remain incomplete because many studies were still undergoing peer review, publication, and indexing at the time of data collection (up to June 2026). Consequently, the publication count for 2026 does not yet represent the total number of studies expected to be published throughout the year.

Beyond the increasing number of publications, the literature synthesis also reveals a notable transformation in research characteristics over the past decade. Early studies primarily concentrated on developing AI algorithms to improve audit efficiency and automate audit procedures. As AI models became increasingly sophisticated, research attention gradually shifted toward issues related to model validity, interpretability, data quality, explainability, and the reliability of AI-assisted decision-making. This transition is evidenced by the growing number of studies integrating machine learning algorithms with statistical techniques, including regression analysis, hypothesis testing, Bayesian inference, and probabilistic modeling, to improve predictive performance while simultaneously providing statistically robust evidence to support AI-generated outcomes.

These findings indicate that contemporary AI research in auditing is no longer exclusively concerned with improving algorithmic accuracy but has increasingly focused on developing intelligent auditing systems capable of producing transparent, explainable, and evidence-based decisions. Statistical methodologies have become an essential component of this development by providing rigorous mechanisms for model validation, uncertainty quantification, performance evaluation, and reliability assessment. Consequently, statistical analysis serves not only as a complementary analytical tool but also as a fundamental framework for enhancing the credibility and trustworthiness of AI applications within the auditing profession.

Overall, the synthesis demonstrates that research on the integration of artificial intelligence and statistical methods in auditing has expanded substantially during the 2017–2026 period. Although studies combining AI with statistical methodologies remain fewer in number than those focusing solely on AI applications, publication trends indicate consistent and sustained growth. This development suggests that the academic community increasingly recognizes the importance of integrating statistical principles with artificial intelligence to develop auditing systems that are not only more efficient and accurate but also exhibit greater transparency, interpretability, robustness, and reliability. This shift in research emphasis provides the conceptual foundation for the subsequent discussion regarding the implementation of statistical concepts in the development of AI-based auditing systems.

The results of the literature synthesis show that the application of Artificial Intelligence (AI) in auditing is still dominated by the need for fraud detection, followed by compliance, model interpretability (explainability), and risk assessment (risk assessment). This distribution indicates that AI research in auditing is no longer focused only on improving predictive capabilities, but also on developing systems that can support auditor decision-making in a transparent manner and in accordance with regulatory demands. Various studies have shown that machine learning, ensemble learning, and deep learning algorithms can improve the accuracy of fraud detection and risk assessment, while the application of Explainable Artificial Intelligence (XAI) through SHAP and LIME increases model transparency so that the analysis results are more easily understood and trusted by auditors (Dash et al., 2025; Ganapathy, 2025; Gaddapuri, 2025; Chen et al., 2025; Sodnomdavaa & Lkhagvadorj, 2025). Furthermore, the integration of AI with cloud computing technology, Robotic Process Automation (RPA), and ERP systems supports the implementation of continuous auditing and real-time compliance monitoring, thereby increasing audit process efficiency (Yadava et al., 2025). Overall, this distribution indicates that the direction of AI development in auditing is increasingly moving towards systems that are not only accurate in detecting irregularities but also transparent, adaptive, and capable of supporting data-driven audit governance.

Method Needs in Auditing

The synthesis results show that statistical methods play a broad role in supporting the development of AI for auditing. Various statistical concepts are used not only to build predictive models but also to validate algorithm performance, measure risk levels, improve model interpretability, and support continuous governance and auditing. Regression analysis, hypothesis testing (Chi-Square and ANOVA), and Bayesian inference are the most widely used methods in various studies because they provide a quantitative basis for AI-generated results (Celestin, 2024; Giri et al., 2025a, 2025b; Giudici et al., 2024; Derks et al., 2022; Toraldo & Priuli, 2022). These findings indicate that statistical methods are no longer positioned as supporting analytical tools, but have become fundamental components in improving the validity, reliability, and objectivity of AI-based audit systems. Thus, the integration of AI and statistics is becoming an increasingly important approach to producing more accurate, transparent, and accountable audit systems.

Benefits of AI and Statistics Integration in Auditing

Synthesis results show that the integration of Artificial Intelligence (AI) and statistical methods significantly contributes to improving audit quality. Statistical methods not only serve as analytical tools but also support the development, validation, and interpretation of AI models, resulting in a more accurate, objective, transparent, and efficient audit process. The combination of machine learning with regression analysis, hypothesis testing, Bayesian inference, and Explainable Artificial Intelligence (XAI) has been shown to improve the reliability of data-driven audit systems.

This integration improves the accuracy of fraud detection, risk assessment, and anomaly detection. Models based on ensemble learning, artificial neural networks, and hybrid approaches have reportedly achieved accuracy exceeding 90% in some audit cases (Dash et al., 2025; Chen et al., 2025). Regression analysis strengthens predictive ability by identifying relationships between financial ratios and potential fraud (Celestin, 2024; Giri et al., 2025a, 2025b), while Bayesian inference supports more adaptive risk assessment and audit sampling based on prior knowledge (Derks et al., 2022; Toraldo & Priuli, 2022; Antwi et al., 2024).

In addition to improving accuracy, statistical methods also strengthen the objectivity of decision-making through hypothesis testing (Chi-Square and ANOVA), which provides a quantitative basis for evaluating AI model performance (Giri et al., 2025a, 2025b; Giudici et al., 2024). On the other hand, the application of XAI through SHAP, LIME, and counterfactual explanations improves model interpretability, making AI decisions more understandable and trustworthy, and meeting audit accountability requirements (Sodnomdavaa & Lkhagvadorj, 2025; Ganapathy, 2025; Gaddapuri, 2025).

The integration of AI with cloud computing, federated learning, ERP, and Robotic Process Automation (RPA) supports continuous auditing, real-time monitoring, and operational efficiency, while statistical methods ensure the validity and accountability of analysis results (Yadava et al., 2025). Furthermore, the application of regression, Bayesian inference, and XAI strengthens AI governance by increasing the transparency, consistency, and accountability of audit models (Kareem, 2025).

Overall, the integration of AI and statistical methods provides multidimensional benefits, including improved accuracy, decision-making quality, transparency, efficiency, and data-driven audit governance. These findings confirm that statistical methods are a fundamental component in the development of AI that is capable of producing audit systems that are more reliable, explainable, and in accordance with the principles of audit professionalism.

Challenges of Implementing Statistical-Based AI in Auditing

Although the integration of Artificial Intelligence (AI) and statistical methods offers numerous benefits to the audit process, the synthesis of results indicates that its implementation still faces technical, organizational, and regulatory challenges. These challenges include data quality, model interpretability, the complexity of integrating AI and statistics, auditor competency, and AI governance. Data quality and availability are key challenges because most AI models are still developed using simulated or limited datasets, so their generalizability to real-world audit conditions remains to be proven. Furthermore, heterogeneity of data sources, format inconsistencies, imbalanced datasets, training data bias, and data drift have the potential to degrade model accuracy and require regular updates and validation (Antwi et al., 2024; Ahmed & Japee, 2025).

Another challenge relates to the interpretability of AI models. Complex algorithms, particularly deep learning, still produce black-box models that are difficult for auditors to understand (Müller et al., 2022). Although explainable artificial intelligence (XAI) approaches such as SHAP, LIME, and counterfactual explanations have improved transparency (Gaddapuri, 2025; Lee, 2021; Dash et al., 2025), their implementation still faces limitations such as varying explanation quality, auditor skepticism, and a trade-off between accuracy and interpretability (Gu et al., 2025). From a methodological perspective, the integration of regression analysis, hypothesis testing, Bayesian inference, and machine learning improves model performance but also increases the complexity of system development and evaluation. Furthermore, differences in data characteristics and audit environments mean that a model that is effective in one organization may not be optimally applicable to another, necessitating validation using real-world and cross-sector data (Bhaumik & Dey, 2023; Derks et al., 2022; Giudici et al., 2024).

The implementation of statistics-based AI is also influenced by organizational readiness and human resources. The changing role of auditors demands competency in statistics, AI, and data analysis, while skills gaps, organizational resistance, infrastructure limitations, and high implementation costs remain major barriers (Ahmed & Japee, 2025; Zisan et al., 2024; Ali, 2025; Derks et al., 2022; Priyo, 2025).

Furthermore, the ethics and governance of AI remain a concern due to lack of uniform regulations, cybersecurity risks, and immature algorithm accountability standards (Kareem, 2025; Desai, 2025). The integration of AI with ERP and Robotic Process Automation (RPA) also requires human oversight mechanisms to ensure accountable decisions (Priyo, 2025). Overall, the challenges of implementing statistics-based AI are multidimensional. Therefore, successful implementation requires support from good data quality, explainable models, enhanced auditor competency, and an adequate governance and regulatory framework to ensure AI-based audit systems can be implemented reliably, transparently, and in accordance with auditing professional standards.

Directions for the Development of Statistics-Based AI in Audit

The synthesis of results indicates that the direction of the development of statistics-based Artificial Intelligence (AI) in audit is no longer solely focused on improving algorithm accuracy, but also on developing more transparent, adaptive, and accountable audit systems. This development is driven by increasing data complexity, demands for efficiency, and the need for audit systems that support reliable decision-making. The most frequently proposed development is a hybrid model that integrates machine learning with statistical methods, such as regression analysis, hypothesis testing, and Bayesian inference. This approach can improve predictive accuracy while strengthening the statistical validity and stability of models across various audit contexts (Derks et al., 2022; Giri et al., 2025a, 2025b; Giudici et al., 2024; Toraldo & Priuli, 2022). Furthermore, the development of explainable artificial intelligence (XAI) through SHAP, LIME, and counterfactual explanations is seen as increasingly important to address black-box characteristics, making AI models more transparent, understandable, and meeting regulatory requirements (Sodnomdavaa & Lkhagvadorj, 2025; Ganapathy, 2025; Gaddapuri, 2025; Lee, 2021). Frameworks such as AURORA and the Trustworthy Evaluation Framework (TEF) also point the way toward auditable AI systems. Bayesian methods are expected to further develop through Bayesian adaptive sampling and risk assessment, which can dynamically update probabilities based on new information during the audit process (Derks et al., 2022; Toraldo & Priuli, 2022; Antwi et al., 2024; Chen et al., 2025). Furthermore, future research should expand the use of real-world datasets, longitudinal validation, and cross-sector testing to improve the generalizability of AI models (Taheri & Samavat, 2025).

Future developments also point to the integration of AI with cloud computing, federated learning, ERP, and Robotic Process Automation (RPA) to support continuous auditing, real-time monitoring, and operational efficiency, with statistical methods still playing a role in validating model performance (Yadava et al., 2025; Akhamere, 2024). In addition, strengthening AI governance, implementing human in the loop, and improving auditor competency in statistics, AI, data analysis, and ethics are important agendas to ensure AI implementation remains transparent, accountable, and in accordance with professional standards (Kareem, 2025; Ahmed & Japee, 2025; Ali, 2025; Zisan et al., 2024).

CONCLUSION

This research systematically identified, analyzed, and synthesized the role of statistical concepts in the development of Artificial Intelligence (AI) for auditing through a review of 149 articles from 2017–2026. The results indicate that the development of AI in auditing has experienced significant growth since 2023, accompanied by a shift in focus from simply improving model accuracy to developing more transparent, explainable, and evidence-based audit systems. The most widely applied statistical concepts include regression analysis, hypothesis testing (Chi-Square and ANOVA), and Bayesian inference. These methods play a role in enhancing AI capabilities for fraud detection, risk assessment, audit sampling, anomaly detection, and model validation and interpretability. The integration of AI and statistics has been proven to provide benefits in the form of increased accuracy, objectivity, efficiency, transparency, and the quality of audit decision-making.

However, the implementation of statistics-based AI still faces challenges such as limited data quality, the complexity of model integration, low interpretability of black-box models, gaps in auditor competency, and immature AI regulations and governance. Therefore, the development of AI for auditing needs to be directed towards a hybrid model that integrates AI, statistical methods, Explainable Artificial Intelligence (XAI), and AI governance to produce an audit system that is more reliable, transparent, and in line with the needs of modern audit practices.

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