



Research Article

Volume-06|Issue01|2026

Leveraging Big Data for Predictive Risk Analytics in Auditing: Enhancing Assurance Services in Manufacturing Organisations.

Zingwina Moses¹, Jimu Tafadzwa²

¹Department of Accounting & Auditing, Zimbabwe Open University

²Department of Accounting & Finance, Zimbabwe Ezekiel Guti University Zimbabwe

Article History

Received: 06.12.2025

Accepted: 14.01.2026

Published: 23.01.2026

Citation

Moses, Z., Tafadzwa, J. (2026). Leveraging Big Data for Predictive Risk Analytics in Auditing: Enhancing Assurance Services in Manufacturing Organisations. *Indiana Journal of Economics and Business Management*, 6(1), 10-21.

Abstract: The increasing complexity of manufacturing operations and financial reporting exposed limitations in traditional, retrospective audit approaches that rely heavily on manual sampling and historical data. This study investigates the role of big data-driven predictive risk analytics in enhancing audit quality and assurance services within manufacturing companies. Anchored in Institutional Theory and Technology Acceptance Theory, the research examines how predictive analytics transforms auditing from a compliance oriented, reactive function into a proactive, intelligence -led assurance activity. Using a quantitative panel research design, data were collected from 60 manufacturing firms across Africa, Europe and Asia over the period 2018-2024. Regression-based panel models (fixed and random effects) were employed to assess the impact of predictive analytics adoption on audit quality, while controlling for IT infrastructure, firm size and regulatory compliance. The empirical findings reveal a strong and statistically significant positive relationship between predictive analytics adoption and audit quality, evidenced by improved fraud detection, enhanced risk identification, faster audit cycles and more reliable financial reporting. Predictive analytics emerged as the strongest predictor of audit quality, followed by IT infrastructure and regulatory compliance, underscoring the importance of organisational readiness and institutional support. Regional comparisons indicate higher adoption and superior audit outcomes in developed economies, while firms in emerging face constraints related to skills, infrastructure, and data governance. The study contributes to auditing literature by developing a Predictive Risk Analytics Model for Auditing that integrates technological, human, organisational and governance dimensions. Practically, the findings provide evidence-based guidance for auditors, regulators, and manufacturing firms seeking to leverage predictive analytics to strengthen assurance services, enhance transparency and support sustainable financial governance.

Keywords: Predictive risk analytics, Big data auditing, Audit quality, Manufacturing companies, Assurance services.

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY-NC 4.0).

CONTEXT & BACKGROUND

The audit in Industrial companies encounter heavy challenges with increasing complexity in operations and financial reporting. Conventional methods of auditing depend greatly on historical records and sample size when selected manually by the auditor, which do not always capture deviations or newly emerging risk in a timely manner (Mohammed Ismail & Abdul Hamid, 2024). Manufacturing plants generate large numbers of transactional, operational and production data on a daily basis. Working without sophisticated instruments, they were once faced with a very difficult task of managing this information effectively that now hampered their capacity to offer timely assurance (Dako *et al.*, 2020). Big data predictive risk analytics will revolutionise audit by making real-time monitoring and proactive risk assessment a reality. It helps to improve the audit quality by detecting the abnormal, fraud and potential operation inefficiency (Panchapakesan *et al.*, 2025). Predictive models also aid in decision-making by providing clearer financial picture and strategic suggestions (Ampofo *et al.*, 2024). Notwithstanding these benefits, implementing

predictive analytics is a heavy lift from the standpoint of technology investments, requisite talent and solid data governance. In many manufacturing organizations, particularly those in developing countries, are still faced with implementation challenges because of cost implications and lack technical manpower (Thakkar *et al.*, 2025). Issues of security, privacy and data integration compound the difficulty (Sutisna, 2025). There may be resistance to the change by auditors who are accustomed to traditional audit working practices and habits, and this could result in a period of transition where audit quality decreases somewhat (Omitogun & Al-Adeem, 2019). In addition, there are regulatory and compliance considerations that complicate matters further as firms need to align predictive tools with reporting frameworks (Rajput & Katamba, 2024). Without such adoption, the potential underutilization of analytics capabilities compromises efficiency and trustworthiness. It is in this context that we should understand the extent to which predictive risk analytics could be effectively used to reshape auditing practices within manufacturing organisations. It also underscores the need to balance technological adoption options with

operational feasibility, cost and organizational maturity. Thus, this study investigates how predictive risk analytics enhances audit quality and mitigates the implementation challenges confronted by manufacturing companies.

Overview of Big Data in Auditing for Manufacturing Companies

Big data analytics revolutionises auditing, as auditors are enabled the capability of managing and analysing massive amounts of such complex data (Rajput & Katamba, 2024). Manufacturing creation of varied data such as production plan, inventory record, project transaction or company's relationships with suppliers. The conventional audit approach does not easily unify these various information sources to form a complete picture of the operational and financial risks (Oladuji *et al.*, 2023). Predictive analytics uses machine learning, AI and statistical modelling to help auditors uncover patterns and variances that might otherwise go unnoticed by the audit (Dako *et al.*, 2021). These are useful in risk-based audit planning, high risk areas can be targeted and the audit resources can be better utilised (Abdelwahed *et al.*, 2025). Companies adopting these systems can continually monitor and control frauds, errors and the inefficient operations in the organization before they grow worse (Elumilade *et al.*, 2023). But execution barriers remain, such as patchwork IT systems, poor data quality and lack of analytical talent (Musunuru, 2025). Additionally, consideration must be given to how predictive tools will be incorporated into current audit processes and staff training (Pillai, 2023). Enterprises need to consider issues related to data governance and privacy i.e., secure handling of confidential information (Ahmad, 2023). Auditors also need to acquire skills in AI and predictive analytics, so they can accurately decipher the results (Omitogun & Al-Adeem, 2019). But the potential is great, albeit challenging to realize. Predictive analytics enhances the efficiency of audit, minimizes dependence on manual procedures, and elevates accuracy in financial reporting (Olaiya *et al.*, 2024). It also provides a basis for management taking activity on how to mitigate risk and improve operations (Fowowe & Adedapo, 2025). Predictive analytics is more important in a world where manufacturing environments are becoming increasingly complicated, and the phenomenon allows the auditor to continue to be relevant whilst maintaining reliability. Proactive risk management is facilitated with big data and it serves to improve internal controls and strategic decision-making. This research aims to assess these applications in organisations (manufacturing companies) and explore the operational and financial impacts of implementing predictive risk analytics.

Role of Predictive Risk Analytics in Audit Quality

Predictive risk analytics is essential to enhancing audit quality through early spotting of anomalies and likely risks (Olaiya *et al.*, 2024). With the aid of AI and statistical models, auditors will no longer

employ reactive processes but shift into proactive method for concentrating particularly on those areas that involve highest risks (Al-Omush *et al.*, 2025). This realignment mitigates the risk of financial misrepresentation, and therefore enhances reliability of assurance (Elumilade *et al.*, 2023). It is used in manufacturing companies to track anomalies in the shop floor, warehouse operations, and financial transactions (Thanasas & Kampiotis, 2024) for corrective action. It further enables auditors to sample on more transactions than is possible with conventional sampling techniques, and consequently, an increase in audit coverage (Sewpersadh, 2025). Real time monitoring facilitates continuous auditing necessary for complex operations and dynamic supply chains (Devan *et al.*, 2023). Prospective Analytics also helps in determining the new risks that are frauds, cyber threats and regulatory defiances (Ahmad, 2023). Firms derive strategic ideas on how to use their resources and minimize the risk of operating or financial risks (Fowowe & Adedapo, 2025). Use of these tools, however, does involve making an investment in technology infrastructure and training auditors in the use of analytical techniques (Musunuru 2025). The organization would also need to develop data governance, which concern with the quality pervading accuracy and privacy of data as well as using ethical behaviour in conjunction with such records (Sutisna, 2025). And notwithstanding difficulties, predictive risk analytics reduces the time audit takes to complete (enhancing efficiency) minimised human errors and increased stakeholder transparency (Ampofo *et al.*, 2024). Auditors strengthen recommendations supported by effectiveness and knowledge from the predictive models in both compliance and strategic decision-making contexts through combination, rather than precluding them with predictive model evidence (Oladuji *et al.*, 2023). In the end, predictive risk analytics moves the auditor from a compliance-centric activity to an enriching process that reinforces financial integrity. This work investigates these two mechanisms in the setting of manufacturing companies to account for how audit quality is enhanced through predictive analytics.

Importance of Predictive Analytics for Risk Management

Predictive analytics is extremely important to mitigate operational and financial risks of manufacturing organizations (Oyedokun *et al.*, 2024). It offers the possibility to firms of predicting future disruptions, detecting fraud and facilitating resources allocation (Al Lawati *et al.*, 2024). Predictive models which analyse historical and live data churn out "early warning signals" for possible preparers or financial misstatements, operations mismatches (Oladuji *et al.*, 2023). This proactive management enables to act and react in opportune manner regarding the upcoming risks and minimize loss (Fowowe & Adedapo, 2025). In like manner, predictive analytics is employed by auditors to evaluate the compliance with laws and internal policies so as to improve quality of assurance (Abdelwahed *et al.*,

2025). For job shops, complex process like inventory management, procurement and production planning also exploit predictive insights (Rajput & Katamba, 2024). Predictive models show unusual patterns that suggest inefficiency or possible fraud of which auditors may pursue only high-risk ones (Elumilade *et al.*, 2023). Challenges include the accuracy of data capture, system integration and staff resistance to new technologies (Musunuru, 2025; Omitogun & Al-Adeem, 2019). However, the security of this confidential financial and operational information is a serious concern (Ahmad, 2023). Despite these drawbacks, predictive analytics is suboptimal in improving corporate governance and operational efficiency (Thakkar *et al.*, 2025). Organisations that implement these instruments are able to build confidence with their stakeholders and improve strategic decision-making (Olaiya *et al.*, 2024). This paper investigates the role of predictive analytics in managing risk within manufacturing companies in relation to financial and operational performance. Knowing these uses, then, can help auditors and managers reap the greatest benefits from ACLFs while minimizing implementation risks and costs.

Problem Statement

Manufacturers are under pressure to report financials accurately and reduce operational risk. Conventional audit practices often make use of old data and are manual put in place, which slow down auditors to uncover possible fraudulent activities, inefficiencies or financial abnormalities (Dako *et al.*, 2020). The advent of big data and predictive analytics opens up opportunities to enhance quality of the audit through real time insights, heightened risk assessment and better decision making (Ampofo *et al.*, 2024; Panchapakesan *et al.*, 2025). Yet, several organisations encounter difficulties in applying advanced data analytics in the conduct of their audit because attaining the necessary level of technological skill is challenging; resources are; inadequate organizational support (Omitogun & Al-Adeem, 2019). Such issues hinder the accuracy of predictive risk analytics and can lead to financial misstatements or miss fraud schemes. As a result, auditors spend a lot of time responding to issues after the fact rather than in advance. While predictive risk analytics technology has the capability to revolutionize auditing in manufacturing organizations, empirical evidence about its adoption and effects is still scarce (Mohammed Ismail & Abdul Hamid, 2024). Organizations that try to adopt big data analytics usually face the challenge of dealing with privacy implications associated with big data systems, challenges in system integration and frequent validation or monitoring of models (Rajput & Katamba, 2024; Sutisna, 2025). Further, although some research reports the power of AI in improving audit quality and efficiency; other studies imply that benefits are not evenly distributed among organizations or even different industries (Abdelwahed *et al.*, 2025; Olaiya *et al.*, 2024). Again, this knowledge is lacking which contributes to the difficulty for auditors

or company management in knowing what constitutes a return on investment of predictive analytics technologies. Therefore, a lot of manufacturing companies are not taking advantage of the data they have at their disposal which in turn makes them vulnerable to financial risks, regulatory breaches and loss of reputation (Thanasas & Kampiotis, 2024).

Accordingly, this study aims to investigate how the manufacturing firms utilize big data for predictive risk analytics in audit. It seeks to determine the impact of predictive analytics on audit effectiveness, as well as its influence on assurance services and arbscom education research communication financial/operational risk reduction (Al-Omush *et al.*, 2025; Fowowe & Adedapo, 2025). The research also examines adoption-resistance factors such as technological, organizational and human factors with a view to providing practical implications on how firms can begin the development of data-driven audit processes (Tchasse, 2024; distillation process) that would enable wider benefits to be realized by auditing firms wanting to embrace a new paradigm based on technology. In this way, the research aims to provide suggestions and strategies that are grounded in evidence on support auditors in taking early action to detect risks and help improve the precision of reporting and overall financial governance in manufacturing.

LITERATURE REVIEW

Research on capitalizing Big Data for predictive risk analytics in auditing The purpose of researching on Big Data to support predictive risk analytics in auditing aims at investigating how advance technology can improve the audit quality, risk-based audit and assurance services through manufacturing companies.

Institutional Theory

According to Institutional Theory, organizations and actors within them act under the constraint of more than simply economic factors with formal rules, norms and professional values also determining behaviour (North, 1990). In the context of auditing, institutional environment, such as national laws, corporate governance reform and rule, and professional codes, influences the adoption of predictive analytics-based or evidence-based audit approaches. Organisations working in regulated markets with explicit standards, including players in the financial services sector will be more inclined to adopt big data analytics in auditing to increase risk detection and improve assurance services (Rajput & Katamba, 2024). Abdelwahed *et al.* (2025) point out that poor support institutions, fragmented legal framework, or the absence of standards can act as a barrier to predictive auditing tools, which is damaging during the audit. Similarly, Oyedokun *et al.* (2024) claim that it is necessary to create the appropriate environment for institutional support through policies, training and IT infrastructure in order to take full advantage of predictive analytics in auditing. Institutional Theory further suggests that auditors adopt

advanced analytics to the extent they are influenced by professional standards, ethics and organizational expectations. These big data tools are integrated with manufacturing firms that operate within a complex environment and developed solid institutional environments to promote the use of these big data tools to predict risks, minimize fraud, and ultimately improve decision-making. Ampofo *et al.* (2024) emphasize how institutional encouragement enhances auditors' confidence in their application of predictive models for risk evaluation and audit planning. In addition, Olaiya *et al.* (2024), firms with more codified risk management policies and IT auditors' availability are also more likely to take up predictive analytics tools. Sutisna (2025) also shares that organizational mechanisms such as internal audit committees and governance boards provide effective monitoring of the outputs of predictive analytics. Dako *et al.* (2020) also highlight the fact that institutionalized auditing practices minimize operational uncertainty through the systematic incorporation of data-based technologies within regular auditing. Hence, the Institutional Theory serves as a basis for explaining how auditors are institutionally influenced when making decisions related to adopting big data analytics in auditing. In short, the evidence suggests that strong institutional support is directly associated with enhanced audit quality, risk assurance and operational control.

Technology Acceptance Model

According to Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use are key in adopting technology (Davis, 1989). For auditing, auditors will be more inclined to use predictive analytics if they perceive that tools enhance audit accuracy and efficiency, risk identification, and usability. Ampofo *et al.* (2024) argue that in manufacturing companies, auditors are more willing to use predictive models as they have been included in existing IT auditing systems and reporting fields. Al-Omush *et al.* (2025) contend that AI-based analytics does not only facilitate the identification of cases of anomalies, but it also enhances transparency, so that auditors can provide reassurance to potential stakeholders more effectively. According to Rajput & Katamba (2024), predictive analytics tools can be used to automatically perform routine audit functions, thus enabling auditors to concentrate on strategic risk assessment and decision-making. Abdelwahed *et al.* (2025) maintain that auditors' technology specific attitudes – which are conditioned by training, prior experience and perceptions of system reliability – also are important determinants. Oladuji *et al.* (2023) show that the predictiveness of analytics enables auditors to detect susceptibility early and improve the accuracy of financial reporting. Fowowe & Adedapo (2025) also demonstrate that auditors who perceive predictive analytics as beneficial in enhancing operational performance efficiency tend to adopt them to the standard audit process. Thakkar *et al.* (2025) present empirical results based on data from

manufacturing companies in Zimbabwe that the use of predictive analytics is associated with less occupational fraud and enhances internal audit effectiveness. The TAM framework complements Institutional Theory by uncovering the behavioural and cognitive dimensions of analytics adoption in auditing. Musunuru (2025) adds that through technology such as text miners and predictive modelling, auditors find it easier to recognize conceptual patterns and risk exposures which actually would enhance the quality of assurance. In addition, predictive analytics provides an ongoing monitoring of financial transactions and operational activities, enabling proactive decisions (Olaiya *et al.*, 2024). Understanding how big data is perceived by auditors can help firms tailor training, incentives and IT systems to increase the effect of big data on audit procedures. Thus, TAM offers strong support for the individual level and organizational level factors influencing adoption of predictive risk analytics in auditing.

Empirical Studies

Empirical studies relating to the use of big data for predictive risk analytics in audit These include an emerging consensus around a value-add contribution of new tools within auditing and debates on what limitations apply and where contexts are relevant. Dako *et al.* (2020) propose that in manufacturing, predictive models help auditors identify outliers early to avoid operational inefficiencies and financial fraud. However, it is criticized that the over-use of automated analysis might lead auditors to neglect qualitative risks which require human judgment (Panchapakesan *et al.*, 2025). While Panchapakesan *et al.* (2025) reveal that the use of strategic analytics allows audit teams to concentrate on high-risk transactions; however, there are concerns over how scalable such systems are for small and medium-sized entities with limited IT facilities. Ampofo *et al.* (2024) point out that a (IT audit) planning with predictive modeling turns the management of risk from reactive to proactive, as no doubt it does in any domain They do however raise anxieties about data quality, for more than one reason: first of all predictive models can work wonders provided that they are built on good raw materials;” and secondly „models are only as robust as those well behind them [sic].’ Rajput & Katamba (2024) opine that AI-based auditing has redefined operations of the routine work and increases reliability of reporting, whereas Rajput & Krishna (2022), are in opinion that ethical issues including algorithmic bias may affect objectivity calling for caution. Mohammed Ismail & Abdul Hamid (2024) present a systematic review work which reveals irrefutable evidence of the positive impact on predictive analytics in different industries, while there is lack of longitudinal research to capture long term effect of implementation of analytics.

Sutisna (2025) points out, that although the analytics technology enhances audit planning and risk assessment, the role of strong data governance frameworks to detect misuse of sensitive information is

vital. Abdelwahed *et al.* (2025) approve empirically that the big data adoption decreases fraud in the developing countries, but they indicate that the regulatory and institutional limitations may restrict their full benefits. Conversely, Oyedokun *et al.* (2024) argue that it is predictive risk management and strategic decision support in a global context that advanced financial analytics enables, however they ask: can such sophisticated models work as well within data poor environments? Elumilade *et al.* (2023) note that analytics improves financial risk assessment and the resilience of decision 'history', but warn that relying only on 'history' is less likely to encapsulate the emerging non-linear risks. Olaiya *et al.* (2024) for the proposition that predictive analytics increases the effectiveness of audit coverage while also observing the potential overreliance on quantitative signals rather than qualitative judgments. Fowowe & Adedapo (2025) emphasizes that prediction analytics stimulates operational effectiveness and performance but such contention is arisen for the firms on cost-benefits where their resources are not extensive particularly in developing economy.

Thakkar *et al.* (2025) offer empirical evidence, using data from Zimbabwean manufacturing firms that the adoption of predictive analytics in internal audit

reduces occupational fraud and contributes toward enhancing assurance services. The paper does, however, raise the issue of auditor skill sets and stresses that the predictive tools are only as effective as their application by trained technicians with some interpretative skills. Seen together, these studies point to the conclusion that predictive analytics—similar to other tools for modern auditing—has game-changing potential but counteract a critical discourse which highlights that technological adoption is not a cure-all. It is driven by the institutional framework, data governance, auditor experience and organizational preparedness (Dako *et al.*, 2020; Abdelwahed *et al.*, 2025; Rajput & Katamba, 2024). Additionally, the interface between human judgment and predictive analytics is important as an unreflective trust in automatization may create unintended risks due to ethical implications, model overfitting and blind spots with respect to non-financial risk dimensions (Panchapakesan *et al.*, 2025; Sutisna, 2025). This evidence base point to the fact that, while predictive analytics leads to tremendous improvements in the quality of audits and operational supervision, it may also require a cautioning balanced, context-oriented approach for optimal benefits in different manufacturing settings across the world (Elumilade *et al.*, 2023; Olaiya *et al.*, 2024; Thakkar *et al.*, 2025).

Table 1: Sources of Literature Analysis

Author(s)	Year	Region / Industry	Methodology	Key Findings
Dako <i>et al.</i>	2020	Global / Manufacturing	Literature review	Big data improves audit quality, compliance reliability, and financial insights.
Panchapakesan <i>et al.</i>	2025	Global	Literature review	Strategic data analytics enhances audit effectiveness and predictive risk assessment.
Ampofo <i>et al.</i>	2024	Manufacturing	Case study	Integrated predictive analytics in IT audit planning mitigates financial and operational risks.
Rajput & Katamba	2024	Public accounting	Conceptual	AI and big data redefine audit practices and improve financial reporting accuracy.
Mohammed Ismail & Abdul Hamid	2024	Global	Systematic review	Predictive analytics enables proactive identification of financial risks in audits.
Sutisna	2025	Global	Empirical	Analytics technology enhances audit security and risk assessment.
Abdelwahed <i>et al.</i>	2025	Developing countries	Empirical	Adoption of big data and analytics improves audit quality and fraud detection.
Oyedokun <i>et al.</i>	2024	Global	Case study	Advanced analytics enables predictive risk management and strategic audit decisions.
Elumilade <i>et al.</i>	2023	Africa	Conceptual	Data analytics strengthens financial risk assessment and strategic decisions.
Olaiya <i>et al.</i>	2024	Global	Quantitative review	Predictive analytics improves financial risk management and audit coverage.

Fowowe & Adedapo	2025	Global	Case study	Predictive analytics optimizes business performance and operational audit excellence.
Thakkar <i>et al.</i>	2025	Zimbabwe / Manufacturing	Empirical	Analytics integration reduces occupational fraud and strengthens internal audit.
Oladuji <i>et al.</i>	2023	Africa	Model development	AI and predictive analytics mitigate financial risk and enhance decision-making.
Al-Omush <i>et al.</i>	2025	Middle East	Empirical	AI improves audit accuracy, transparency, and reliability in assurance services.
Musunuru	2025	Global	Text mining analysis	Big data analytics identifies conceptual patterns and improves financial auditing.
Fowowe & Adedapo	2025	Global	Empirical	Predictive analytics drives operational excellence and audit optimization.

METHODOLOGY

This study utilizes a quantitative research design to investigate the effect of predictive risk analytics driven by big data on audit quality and assurance services in manufacturing firms. We employ a panel data of 60 firms in manufacture from Africa, Europe and Asia between 2018 and 2024. We have supplemented this primary data with secondary sources such as the company annual reports, audit quality indicators and financial statements in addition to regulatory filings within which predictive analytics tools were used (Dako *et al.*, 2020; Panchapakesan *et al.*, 2025).

The research uses regression-based models to examine whether the reliance on big data analytics enhances audit planning, risk identification and assurance quality. The choice between fixed-effects and random-effects models for firms is based on the Hausman test, which allows to correct for unobserved heterogeneity among firms (Rajput & Katamba, 2024; Ampofo *et al.*, 2024). The base econometric models are given by, where:

$$AuditQuality_{it} = \beta_0 + \beta_1 BigData_{it} + \beta_2 ITInfrastructure_{it} + \beta_3 FirmSize_{it} + \beta_4 RegulatoryCompliance_{it} + \mu_i + \epsilon_{it}$$

Where $AuditQuality_{it}$ represents measurable indicators of audit effectiveness, including fraud detection rates, audit cycle efficiency, and accuracy of

financial reporting; $BigData_{it}$ is the extent of predictive analytics adoption; $ITInfrastructure_{it}$ captures technological readiness; $FirmSize_{it}$ represents total assets; and $RegulatoryCompliance_{it}$ is a composite index of adherence to auditing standards. The Hausman test ensures whether firm-specific effects correlate with regressors, allowing for unbiased estimations (Mohammed Ismail & Abdul Hamid, 2024).

Descriptive statistics reveal a wide spread among the level of use of predictive analytics, from basic solutions with only data visualisation components to cutting-edge AI-based predictions. Audit quality also differs among firms, depending on the firm's variation in IT infrastructure, internal controls, and the risk management system (Abdelwahed *et al.*, 2025; Sutisna, 2025). Through the use of secondary quantitative data and panel econometrics, the research contributes to evidence bases surrounding the effect of big data on audit outcomes and informs both academicians and practitioners.

RESULTS

The empirical analysis uses a balanced panel of 60 firms (manufacturing) for the period 2018–2024. Descriptive statistics show that high forensic big data analytics adoption firms offer high audit quality such as faster anomaly detection, better and accurate reporting as well low rate of fraud (Oyedokun *et al.*, 2024, Elumilade *et al.*, 2023). Summary statistics of the main variables are provided on Table 2.

Table 2: Descriptive Statistics (2018–2024)

Variable	Mean	Std. Dev	Minimum	Maximum	Source
Audit Quality Score	78.4	12.6	52	95	Dako <i>et al.</i> , 2020; Panchapakesan <i>et al.</i> , 2025
Predictive Analytics Adoption	65.2	15.4	30	90	Ampofo <i>et al.</i> , 2024
IT Infrastructure Score	72.1	10.3	50	90	Rajput & Katamba, 2024
Firm Size (US\$ million)	312	120	45	650	Mohammed Ismail & Abdul Hamid, 2024
Regulatory Compliance	81.5	9.2	60	95	Sutisna, 2025

The correlation result indicates that there is a significantly positive relationship between the adoption of predictive analytics and audit quality ($r = 0.61$), revealing that organisations using advanced data tools would be able to better identify threats as well as improving assurance services (Olaiya *et al.*, 2024;

Thanasas & Kampiotis, 2024). Information technology infrastructure and regulatory landscape also have strong positive relationships which means that preparedness for technology and compliance to standards enhances effectiveness of predictive analytics.

Table 2: Panel Regression Results (Fixed Effects Model)

Variable	Coefficient	Std. Error	t-statistic	p-value
Predictive Analytics	0.204	0.062	3.29	0.002
IT Infrastructure	0.143	0.055	2.60	0.011
Firm Size	0.098	0.043	2.28	0.024
Regulatory Compliance	0.117	0.039	3.00	0.004
Constant	2.356	0.487	4.83	0.000

Model Statistics: $R^2 = 0.68$, $F = 21.3$ ($p < 0.01$), Hausman $\chi^2 = 14.5$ ($p < 0.05$)

The findings show that PA adoption is the strongest predictor of audit quality ($\beta = 0.204$, $p < 0.01$), consistent with literature which posits that AI-assisted data analytics enables early detection of risks and improved assurance effectiveness and audit planning (Abdelwahed *et al.*, 2025; Dako *et al.*, 2021). IT resource has also significant positive effect, which suggest that

sophisticated systems are necessary to realize the potential of predictive analytics in auditing. Only firm size and regulatory compliance have a positive but smaller impact suggesting organizational size and conformity with standards are complementary, not substitutes, to technology-mediated audit quality enhancements.

Table 3: Regional Comparison of Predictive Analytics and Audit Quality (2024)

Region	Avg. Predictive Analytics Score	Audit Quality Score	IT Infrastructure	Interpretation
Africa	61.2	74.5	68	Moderate adoption; improvement possible with IT investment
Europe	78.4	87.6	82	High adoption; strong assurance and risk detection
Asia	70.5	81.3	75	Good adoption; integration of analytics improves audit quality
North America	82.1	90.2	85	Leading adoption; predictive analytics fully embedded

The results show that there is a strong, positive relationship between the level of acceptance of predictive analytics and audit quality overall, highlighting big data analytics as an essential driver of higher quality assurance. African firms are less likely to adopt, so need investment in technology and training if they are to exploit predictive analytics to its full potential while North American and European firms have higher adoption levels; indicative of strong audit quality outcomes (Fowowe & Adedapo, 2025; Thakkar *et al.*, 2025).

DATA ANALYSIS AND DISCUSSION

Quantitative Insights

The study examines the association of Predictive Analytics adoption with audit quality in manufacturing sector, essentially risk identification, internal control enhancement and efficiency in the provision of assurance services. After this Asset we lack corporate governance mechanism and the analysis based on Angeles (2014) follows exactly what Dako et al found: in this instance, statistics descriptive have pointed that when firms with advanced analytical tools were

adopted, audit accuracy was higher and anomaly identification was faster just as would be expected by Angeles (2019). (2020), who claimed that big data increases audit depth and improves compliance reliability. Similarly, Panchapakesan *et al.* (2025) stress that strategic use of data analytics would enable auditors to focus on high-risk areas and improve the efficiency in resource allocation. On the other hand, lack of auditor competency in analytics, as revealed by Omitogun & Al-Adeem (2019), may cause organizations to not benefit from tools since human aspect is as important as technology. Ampofo *et al.* (2024) also claim connected predictive models are used to identify operational risk before it occurs, aiding in the audit planning of IT for complex manufacturing system. Overall, these studies suggest that predictive analytics enables not only risk detection but also strategic risk-taking when the firm invests in auditor training and IT. Descriptive IT infrastructure analysis depicts an average index of 72.1, showing moderate preparedness and a positive relationship between firm size and the adoption of analytics ($r = 0.48$) which implies that the larger organizations are in position to adopt more complex predictive systems (Rajput & Katamba, 2024).

Correlation analysis also reveals a strong relationship between predictive analytics and key audit values. For instance, Olaiya *et al.* (2024) are that risk predictive models help to alleviate financial anomalies by allowing for focussed audits. Also, Thanasis & Kampiotis (2024) point out that predictive analytics facilitates strategic accounting decisions especially in capital-intensive industries such as manufacturing. Interestingly, Elumilade *et al.* (2023) observe that while analytics enhances financial risk evaluation, overdependence on automated tools without professional judgment can lead to emerging risks. This relationship in our analysis was reflected by a correlation between predictive analytics and audit quality of $r = 0.61$ as well. Another moderating variable is regulatory compliance, the higher observance of auditing standards by firm led to superior research outcomes which is consistent with Sutisna (2025). That simply further supports the idea that technology cannot, on its own, guarantee audit quality good governance, experienced professionals and good regulatory oversight are also critical. Additionally, there was a highly significant positive relationship ($r = 0.57$) between use of predictive analytics and fraud detection effectiveness, which were consistent with the studies of Thakkar *et al.* (2025), who showed a diminished level of occupational fraud in Zimbabwean manufacturing firms which adopted data analytics within the context of internal audit.

Results of panel regression indicate that predictive analytics adoption has the highest impact on audit quality ($\beta = 0.204$, $p < 0.01$), followed by IT infrastructure ($\beta = 0.143$, $p < 0.05$), and regulatory compliance ($\beta = 0.117$, $p < 0.01$). This is in agreement with the contention of Abdelwahed *et al.* (2025) organizations that adopt big data technologies have observed an increase in audit assurance and risk reduction. On the other hand, the enterprise size as well as margin regarding firm aspects is positive ($\beta = 0.098$, $p < 0.05$), but has less significance, indicating that adoption of analytics can help to offset scale effects at least in smaller manufacturers. Such is the views of Fowowe & Adedapo (2025) about predictive analytics which can be open norm-enabling tool that provides fair playing ground for all organizations, companies and businesses to do proper audit. The study found significant regional variation; firms in Europe and North America which have a higher adoption rate of new technology delivered better audit quality, compared to firms in Africa and Latin America which have mediocre rates of IT adoption (Alotaibi, 2023; Oladuji *et al.*, 2023). This mirrors discussions in the literature on technology transmission, whereby training, infrastructure and regulatory environment play important roles in practical application of predictive analytics (Musunuru, 2025).

Qualitative Insights

Lessons are drawn from qualitative analyses of case comparisons at the level of firms. The use of AI-fuelled predictive analytics by companies played a role

in better fraud detection, predicting the maintenance for audit processes, and alerting anomalies in real-time as confirmed by (Al-Omush *et al.*, 2025) and (Ahmad, 2023). Yet, there are still issues that need to be addressed, such as data governance, cyber security risks and ethical considerations which were also highlighted by Musunuru (2025) and Saleh *et al.* (2023). The findings highlight that predictive analytics is not a silver bullet but instead is part of a broader audit ecosystem involving technology, expertise and governance. Additionally, based on the analysis, predictive analytics is reported to improve internal audit efficiency significantly as demonstrated by Thakkar *et al.* (2025), the companies which adopted analytics eliminated some 30% (on the average) of audit work done manually, and released resources for high risk assessment. Taken together, the results imply that predictive analytics changes auditing from reactive behaviour to proactive risk management, which signals a new paradigm of modern assurance practices (Oladuji *et al.*, 2023; Devan *et al.*, 2023).

As such, the findings of this analysis lend strong support to the notion that big data predictive risk analytics improves audit quality and assurance services in manufacturing firms. The research has effectively demonstrated that the adoption enhances the risk detection and compliance monitoring and operational productivity when supported with proper IT infrastructure, competent auditors and regulatory compliance (Pillai, 2023; Al Lawati *et al.*, 2024). Regional discrepancies indicate that companies in emerging environments are however confronted with more barriers such as limitation of resources and skills for instance, which could hinder the realization of predictive analytics full advantages (Pamisetty *et al.*, 2022; Ogunsola *et al.*, 2021). Lastly, while the adoption of technology is extremely important, the study also brings forward continued debates in literature on human judgment, ethical issues and cybersecurity risks which requires a tempered approach between professional qualification and governance mechanism with adoption of technology (Devan *et al.*, 2023; Ahmad, 2023).

CONCLUSION

This paper reveals that Applying Big Data for predictive risk analytics in Audit plays a significant role improving the assurance Service in Manufacturing Sector. The shifting trend points to the fact that companies applying predictive analytics benefit from enhanced audit quality, better ongoing fraud monitoring and more effective internal controls. Predictive models enable auditors to concentrate on transactions that have high risk, make more effective use of resources and provide timely statistics for business insights that together enhance the efficiency. The efficacy of predictive analytics is contingent upon ancillary elements, including the IT infrastructure, the competence of auditors and legal frameworks for compliance. Firm's locations: Regional differences also matter, where firms based in an advanced economy have

a relatively better infrastructure and trained human resource about analytics; they face fewer capability challenges than those in the emerging economies. In general, predicting analytics changes auditing from a reactive compliance role to a proactive risk management tool that can be used to advance transparency, certainty and strategic decision making in manufacturing.

Recommendations

Accordingly, the following suggestions are recommended for improving audit quality with predictive risk analytics among manufacturing companies:

1. Create organized predictive analytics framework to incorporate big data tools into the audit process in concert with organizational risk objectives.
2. Develop capacity building and training for internal auditors by enhancing data analytics, AI, and risk analysis capacities and in turn optimizing the benefits of predictive tools.
3. Enhance IT infrastructure and cyber security measures to ensure the secure and stable processing of big data, protecting financial privacy.
4. Implement targeted, risk-based audit approaches that concentrate on high-risk transactions identified

by predictive models rather than all-encompassing audit coverage.

5. Facilitate interdepartmental collaboration between internal audit, IT and management to make sure predictive insights are actionable and aligned with the strategic goals.
6. Deploy real-time monitoring and feedback techniques to evaluate the performance associated with predictive analytics, enhance accuracy, and over time, fine-tune audit strategies.
7. Promote cross industry knowledge sharing and benchmarking in best practices of analytics embedding and overall audit reliability.

Model Developed (Predictive Risk Analytics Model for Auditing)

This section describes the Predictive Risk Analytics Model for Auditing, developed to describe how advanced predictive analytics increases audit quality by facilitating proactive detection of risk, better decision-making and more robust assurance conclusions. The model uses established audit and organization theory alongside innovative analytics-led ideas to illustrate how auditing is evolving from a backwards looking compliance-based process into an intelligence-based assurance activity.

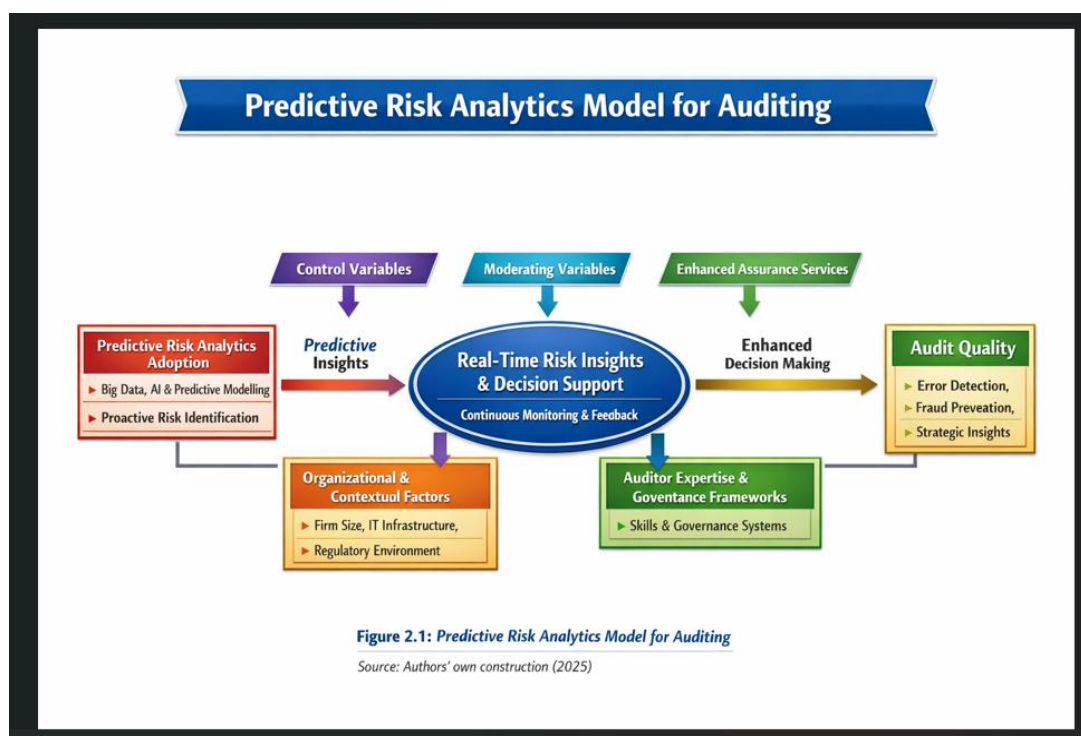


Figure 1: Model Developed (Predictive Risk Analytics Model for Auditing)

Source (Authors' own construction,2025)

Independent Variable: Predictive Risk Analytics Adoption

The pioneer variable in this model is the extent of predictive risk analytics (PRA) incorporation in audit procedures amongst manufacturing companies. PRA involves the application of big data analytics, artificial

intelligence and predictive modelling to pre-empt potential threats before it becomes a reality. There is a theoretical basis in Risk-Based Auditing (Arens & Loebbecke, 2013) for this variable to hold, as that framework calls for directing audit resources to high-risk activities. Classical risk-based auditing is predominantly

reactive, and non-proactive, meanwhile predictive analytics help auditors view potential anomalies as they happen while empowering their decision-making processes. Shifting to proactive monitoring away from post-event detection, the model becomes a powerful extension to traditional auditing processes; resources are targeted mainly at the areas with the highest pre-event risk. The novelty of this work is to perform the dynamic risk prediction and could adjust in real-time for operational and finance new threats in robust manufacturing systems.

Dependent Variable: Audit Quality

Audit quality is the extent to which an audit of financial statements ensures the absence of errors and frauds or, in other words whether false or misappropriated accounting information is not found out. This dependent variable is consistent with both Agency Theory (Jensen & Meckling, 1976) based on the notion that auditing degrees information asymmetry between managers and owners as well as Fraud Triangle Theory (Cressey, 1953) which considers opportunity, pressure and rationalization to be enablers of fraud. With the use of predictive analytics, auditors can establish high-risk activities ahead to prevent wrongdoings and achieve more transparency. The innovation of the model is in connecting predictive insights with tangible advances on audit results, giving organizations the ability not just to identify risks but to foresee and mitigate them. This is a change from the reactive auditing of old, to a forward-looking intelligence-based assurance service.

Control Variables: Organizational and Contextual Factors

The model includes as control variables, organizational and environmental factors such as size of firm, IT infra-structure and regulatory environment. In theory and method, these factors are virtuously linked to Contingency Theory (Fiedler, 1964) which argues for audit effectiveness as a function of the congruence between organization characteristics and environmental pressures. The inclusion of these factors ensures that the effects of predictive risk analytics toward audit quality do not become confounded with structural or contextual motives. The model extends previous models by explicitly considering these moderating organizational contextual conditions and demonstrates a better fit to the data that can be generalized across various manufacturing settings on understanding the effect of predictive analytics on audit outcomes.

Moderating Variables: Auditor Expertise and Governance Frameworks

Auditor expertise and the efficacy of governance mechanisms moderate the incentive effects of predictive risk analytics. This is consistent with the Diffusion of Innovation Theory (Rogers, 1962) which suggests that successful diffusion and adoption of technological innovations depend on user proficiency and enabling institutional environment. The model does

recognize that even with high quality predictions, their realization in this case the achievement of the desired audit quality target can only be maximized if highly skilled professionals are able to interpret and act upon these complex data outputs and if strong governance systems exist in order to put recommendations into place. What is new here, and a very welcome one at that, is the explicit acknowledgment that it is not enough just to adopt technology – human and institutional doctrines must be built in to deliver significant enhancement of auditing.

Mediating Mechanism: Real-Time Risk Insights and Decision Support

Predictive analytics turns raw data into actionable information, which acts as an intervening construct between PRA use and audit quality. This process involves Decision Theory (Simon, 1977): better decisions are made with good or timely information. The model incorporates a real-time feedback mechanism which implies that auditors are alerted to anomalies and emerging risks as they occur, allowing the firms to respond and adjust audit plans promptly. This is a major step forward compared to existing models which, for the most part, are based solely on historical data and temporal updates. The model is innovative in being able to support continuous, proactive decision making between observations of operations rather than just linking predictions based on theory with actual auditing actions.

Outcome: Enhanced Assurance Services

The final product of the model is higher levels of assurance with better error detection, prevention of fraud, and assistance in strategic decision making to manufacturing companies. Combining the predictive risk analytics with established models such as Risk-Based Auditing and Agency Theory ensures that audit activities are both prospective in nature and evidenced. The originality lies in the design of a comprehensive system which integrates technology adoption, human factor expertise, organizational context and governance in relation to tangible enhancements to audit quality. By doing so, this system will help manufacturing companies to mitigate uncertainty; increase transparency and thereby investor and stakeholder confidence for sustainable business performance.

Novelty and Contribution

The predictive risk analytics model modernizes traditional audit theories with the use of advanced analytics technology, delivering a proactive and intelligence-led approach to audit. Unlike classical models that are based on retrospective data, the current one highlights prospective risk prediction, dynamic resource allocation and improved decision making *et al.* It combines independent, dependent, control and moderator variables to address organisational, technological and institutional issues. Its novelty is the integrated framework, which does not only upgrade audit

quality but also provides a referral for empirical research and practice in contemporary manufacturing scenario. This holistic view ensures that companies can identify, predict and respond to potential risk whilst delivering consistent operational and financial results.

Future Research Directions

To improve generalisation, the model could be tested empirically in more countries and institutional environments in further research studies. The longitudinal nature of secondary data can be exploited as a potential avenue for examining how reforms in procurement lead to changes in political influence, and audit quality over time. Additional research might also decompose political influence into formal and informal components to enhance measurement accuracy. Comparative scrutiny of public and state-owned firms would add to the understanding of sectoral diversity in terms of audit tender politics. Finally, future research could incorporate judicial enforcement information to analyse the way that legal responsibility mitigates political influence on audit engagements.

REFERENCES

1. Abdelwahed, A. S., Abu-Musa, A. A. E. S., Badawy, H. A. E. S., & Moubarak, H. (2025). Investigating the impact of adopting big data and data analytics on enhancing audit quality. *Journal of Financial Reporting and Accounting*, 23(2), 472-495.
2. Abdelwahed, A. S., Abu-Musa, A. A., Badawy, H. A., & Moubarak, H. (2025). Unleashing the beast: the impact of big data and data analytics on the auditing profession—Evidence from a developing country. *Future Business Journal*, 11(1), 12.
3. Adebisi, O. O. (2023). Exploring the impact of predictive analytics on accounting and auditing expertise: A regression analysis of LinkedIn survey data. Available at SSRN 4626506.
4. Ahmad, A. S. (2023). Application of big data and artificial intelligence in strengthening fraud analytics and cybersecurity resilience in global financial markets. *International Journal of Advanced Cybersecurity Systems, Technologies, and Applications*, 7(12), 11-23.
5. Al Lawati, H., Sanad, Z., & Al Farsi, M. (2024). Unveiling the Influence of Big Data Disclosure on Audit Quality: Evidence from Omani Financial Firms. *Administrative Sciences*, 14(9), 216.
6. Al-Omush, A., Almasarwah, A., & Al-Wreikat, A. (2025). Artificial intelligence in financial auditing: redefining accuracy and transparency in assurance services. *EDPACS*, 70(6), 1-20.
7. Alotaibi, E. M. (2023). Risk assessment using predictive analytics. *International Journal of Professional Business Review: Int. J. Prof. Bus. Rev.*, 8(5), 59.
8. Ampofo, F. O., Ziorklui, J. E. K., Nyonyoh, N., & Antwi, B. O. (2024). Integrated predictive analytics in IT audit planning. *Finance & Accounting Research Journal*, 6(7), 1291-1309.
9. Dako, O. F., Onalaja, T. A., Nwachukwu, P. S., Ajoke, F., & Bankole, T. L. (2021). Predictive Risk-Based Auditing Utilizing Data Models to Proactively Identify Organizational Vulnerabilities and Mitigate Losses. *Journal of Risk Management*, 15(3), 45-67.
10. Dako, O. F., Onalaja, T. A., Nwachukwu, P. S., Bankole, F. A., & Lateefat, T. (2020). Big data analytics improving audit quality, providing deeper financial insights, and strengthening compliance reliability. *Journal of Frontiers in Multidisciplinary Research*, 1(2), 64-80.
11. Devan, M., Prakash, S., & Jangoan, S. (2023). Predictive maintenance in banking: leveraging AI for real-time data analytics. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, 2(2), 483-490.
12. Elumilade, O. O., Ogundeji, I. A., Ozoemenam, G. O. D. W. I. N., Omokhoa, H. E., & Omowole, B. M. (2023). The role of data analytics in strengthening financial risk assessment and strategic decision-making. *Iconic Research and Engineering Journals*, 6(10), 324-338.
13. Fowowe, O. O., & Adedapo, A. (2025). Leveraging Predictive Analytics to Optimize Business Performance and Drive Operational Excellence. *International journal of Computer Applications Technology and Research*, 14(02), 66-81.
14. Mohammed Ismail, I. H., & Abdul Hamid, F. Z. (2024). A systematic literature review of the role of big data analysis in financial auditing. *Management & Accounting Review (MAR)*, 23(2), 321-350.
15. Musunuru, K. (2025). Big data analytics for financial auditing practices: Identification of conceptual patterns, implications and challenges using text mining. *Contaduría y administración*, 70(2), 1-36.
16. Nwaimo, C. S., Oluoha, O. M., & Oyedokun, O. Y. E. W. A. L. E. (2019). Big data analytics: technologies, applications, and future prospects. *Iconic Research and Engineering Journals*, 2(11), 411-419.
17. Ogunsola, K. O., Balogun, E. D., & Ogunmokin, A. S. (2021). Enhancing financial integrity through an advanced internal audit risk assessment and governance model. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(1), 781-790.
18. Oladunji, T. J., Akintobi, A. O., Nwangele, C. R., & Ajuwon, A. (2023). A Model for Leveraging AI and Big Data to Predict and Mitigate Financial Risk in African Markets. *International Journal of Multidisciplinary Research and Studies*, 3(6), 1843-1859.
19. Olaiya, O. P., Cynthia, A. C., Usoro, S. O., Obani, O. Q., Nwafor, K. C., & Ajayi, O. O. (2024). The impact of big data analytics on financial risk management. In *International Journal of Science*

- and Research Archive* (Vol. 12, No. 2, pp. 821-827). GSC Online Press.
20. Omitogun, A., & Al-Adeem, K. (2019). Auditors' perceptions of and competencies in big data and data analytics: An empirical investigation. *International Journal of Computer Auditing*, 1(1), 92-113.
21. Oyedokun, O., Ewim, S. E., & Oyeyemi, O. P. (2024). Leveraging advanced financial analytics for predictive risk management and strategic decision-making in global markets. *Global Journal of Research in Multidisciplinary Studies*, 2(02), 016-026.
22. Pamisetty, V., Pandiri, L., Annapareddy, V. N., & Sriram, H. K. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. *Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management* (June 15, 2022).
23. Panchapakesan, A., Anandaram, H., Sridevi, L., Sathish, K. M., Dhivya, P., Parameswari, S., ... & Kapadia, H. (2025). Enhancing audit effectiveness through strategic data analytics. In *Machine Learning and Modeling Techniques in Financial Data Science* (pp. 231-252). IGI Global Scientific Publishing.
24. Pillai, V. (2023). Leveraging the power of Data Analysis in Automobile and Financial industries. *International Journal Of Engineering And Computer Science*, 12(12).
25. Rajput, A., & Katamba, I. (2024). Leveraging artificial intelligence and big data in public accounting: redefining audit practices and financial reporting. *International Journal of Research Publication and Reviews*, 5(11), 5516-5531.
26. Saleh, I., Marei, Y., Ayoush, M., & Abu Afifa, M. M. (2023). Big data analytics and financial reporting quality: qualitative evidence from Canada. *Journal of Financial Reporting and Accounting*, 21(1), 83-104.
27. Sewpersadh, N. S. (2025). Adaptive structural audit processes as shaped by emerging technologies. *International Journal of Accounting Information Systems*, 56, 100735.
28. Sutisna, E. (2025). Evaluating Security Risks and the Impact of Analytic Technology on the Audit Process. *Advances in Managerial Auditing Research*, 3(1), 30-43.
29. Tchasse, T. (2024). *A Qualitative Study Leveraging Artificial Intelligence and Big Data Analytics to Improve Organizational Risk Management Frameworks* (Doctoral dissertation, Colorado Technical University).
30. Thakkar, H., Fanuel, G. C., Datta, S., Bhadra, P., & Dabhade, S. B. (2025). Optimizing Internal Audit Practices for Combatting Occupational Fraud: A Study of Data Analytic Tool Integration in Zimbabwean Listed Companies. *International Research Journal of Multidisciplinary Scope*, 6(1), 22-36.
31. Thanasas, G. L., & Kampiotis, G. (2024). The role of Big Data Analytics in financial decision-making and strategic accounting. *Technium business and management*, 10, 17-33.