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Artificial intelligence and its influence on internal audit analytics

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ABSTRACT

The aim of this study is to explore the impact of artificial intelligence (AI) on internal audit analytics in the private sector of the Kingdom of Saudi Arabia. The sample consisted of 370 internal audit professionals, including audit managers, auditors, data analysts, and financial and accounting staff. A descriptive–analytical approach was adopted, and data were collected using a questionnaire. The results show that the adoption of AI technologies significantly enhances internal auditing processes in Saudi private-sector companies. In particular, descriptive analytics, diagnostic analytics, machine learning, robotic process automation, predictive analytics, and natural language processing all have notable effects on auditing practices. Advanced techniques such as machine learning and predictive analytics are especially effective in identifying discrepancies and improving the proactive role of auditing. In contrast, descriptive and diagnostic analytics, as well as process automation, mainly improve efficiency, speed, and error reduction. Based on these findings, the study recommends increasing investment in AI technologies and integrating them into internal audit strategies. It also highlights the importance of providing specialized training programs to help audit professionals effectively use advanced analytical tools.

1. Introduction

The world is moving toward an era of automation and artificial intelligence (AI), in which the value of data use is greater than ever. AI has already been integrated into the work of several professions and organizations to enhance productivity and efficiency (Shabani et al., 2022). As organizations increasingly implement AI technologies, internal auditing has undergone several developments in risk detection, compliance monitoring, data analysis, and decision-making (Ghafar et al., 2024).

The development of AI functions has the potential to transform the profession of internal audit. Traditionally, internal audits have been defined as a process that provides stakeholders with reasonable assurance through systematic examinations based on sampling procedures (Ali, 2025). AI, however, represents a disruptive technology that has revolutionized how corporations analyze data, identify vulnerabilities, and make decisions. Internal audits are becoming more accurate, efficient, and fraud-resistant using AI technologies, including machine learning (ML), predictive analytics, and natural language processing (NLP). Audit firms increasingly employ data analytics tools in audit planning and implementation (Shabani et al., 2022). For internal audit functions (IAFs), AI can provide strategic control, reduce manual processes, and enable value-added auditing services (Wassie and Lakatos, 2024).

Internal auditors traditionally apply sampling techniques in internal audit engagements, which creates the risk that samples may not accurately reflect the entire dataset (Mpambane and Kunz, 2025). The adoption of audit management software (a data analysis tool) is positively correlated with the effectiveness of internal auditing. As the maturity of internal audit data analytics improves, the quality of audit measures also increases. Internal audit serves as a supportive mechanism for risk management, which is the predominant factor in guaranteeing the quality of financial reporting within government agencies (Almahuzi, 2025). Consequently, IAFs are shifting toward more sophisticated, digitized data analytics, with greater integration and reduced dependence on paper- and spreadsheet-based processes. The adoption of technology, however, remains a central challenge for internal auditing. Technological advancements have made audit

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procedures more effective and efficient. Through computerization and advanced analytics, auditors can reduce manual workloads and errors while accelerating data collection, analysis, and reporting. These tools also enable auditors to provide management with real-time information and recommendations, thereby enhancing organizational performance. Given the growing sophistication and pace of technological change, traditional auditing methods are inadequate for assessing risks and detecting fraud. High-level data analytics offer a radical solution, enabling more efficient risk management and fraud detection (Ilori et al., 2024).

Information-specific IT expertise in IAFs is a strong driver of technology adoption. Similarly, the business understanding and logical thinking of chief audit executives influence adoption, as do organizational cultures that prioritize technological innovation (Islam and Stafford, 2022). Nevertheless, AI integration is not without challenges. Gökoğlan et al. (2025) highlight issues such as inadequate analysis, ethical concerns, and declining security and confidentiality in audit operations, which necessitate new technological control mechanisms. Saud et al. (2025) further argue that effort expectancy, performance expectancy, and social influence strongly shape the adoption of big data analytics in auditing, with performance expectancy emerging as a key determinant.

Despite these challenges, AI tools enable auditors to track large volumes of data and reduce uncertainty, potentially shifting the focus of internal auditing toward providing absolute assurance. This change raises questions about whether the traditional definition of internal audit remains adequate in an AI-driven context (Ali, 2025). However, a recent study has shown that the actual use of data analytics among internal auditors remains relatively low (Mpambane and Kunz, 2025). Although AI has an increasing role in auditing, its potential to revolutionize the goal, approach, and level of assurance of internal auditing is not thoroughly researched, an exceptional situation (Ali, 2025). Current literature gaps include limited empirical studies, low adoption of AI in IAFs globally, and the absence of a comprehensive framework for integrating AI into internal audit (Wassie and Lakatos, 2024).

In Saudi Arabia, research on AI in internal auditing is emerging. For example, Ghozi (2024) investigated the effects of AI use in the Saudi private sector and found a wide gap between proposed applications and actual use, citing data security concerns, shortages of skilled professionals, and inadequate technological support. Jaradat et al. (2025) emphasized the alignment of internal audit automation with Saudi Vision 2030, highlighting its role in enhancing audit effectiveness. Ali (2025) similarly confirmed the potential of AI to improve audit accuracy and efficiency but also notes barriers, including operational and ethical challenges, stakeholder trust, and training needs. Despite its promise, the adoption of AI in internal auditing in Saudi Arabia's private sector faces significant obstacles, including low competency levels, high costs, data privacy concerns, and resistance to change. Empirical evidence on the effectiveness of AI in improving internal audit analytics remains scarce, leaving open the critical question of whether AI enhances auditing performance or introduces new risks and complexities.

This research is valuable because it bridges a gap in current knowledge and practice concerning the role of AI in Saudi Arabia's internal auditors. The findings will inform auditors, managers, and policymakers about the strengths and weaknesses of AI-based analytics. The study also supports Saudi Vision 2030 by advancing digital transformation and offering recommendations to enhance transparency, accountability, and efficiency in internal auditing.

2. Literature review and hypotheses

Recent literature acknowledges that AI has radically transformed internal audit operations, shifting audits toward data-driven processes that are not intended to be compliance-oriented. The use of AI-based audit systems improves the early detection of risks, ongoing monitoring, and testing across the entire population, thereby increasing audit credibility and governance performance. In this sense, AI has been extensively depicted as a driver of effectiveness, precision, and perceptiveness in internal auditing.

However, some scholars challenge this positive assessment and emphasize that implementation faces significant challenges. Although AI enhances fraud detection and prediction, its effectiveness is limited by technical readiness, ethical concerns, and the data quality of auditors (Usul and Alpay, 2025). Multiple articles highlight that, unless reskilled and governance mechanisms are in place, AI-based audits can create new risks, such as algorithmic bias, cybersecurity, and privacy risks. This controversy highlights a contradiction between the technical capabilities of AI and its applicability in real-world auditing contexts.

Moreover, literature indicates an imbalance in the use of various levels of analytics. The uses and applications of descriptive and diagnostic analytics are well known and highly valued for providing immediate value in understanding past trends and pinpointing weaknesses in control. Conversely, predictive and prescriptive analytics, despite their theoretical potential, are not exploited due to high infrastructure costs, data complexity, and a lack of specific skills (Anggraini et al., 2025). This gap highlights a significant research question: whether advanced analytics improve internal audit effectiveness to a greater extent than traditional audit methods.

The other major controversy is about the changing relevance of internal auditors. Although AI automates the repetition, researchers state that AI does not exclude the professional opinion; instead, it reinvents the roles of an auditor as one who interprets, provides a strategic approach, and oversees governance (Popara et al., 2023). However, there remains a lack of empirical studies on the integration of human knowledge and AI-driven information among auditors, particularly in developing economies.

To conclude, although previous studies identify the beneficial effects of AI in internal audit analytics, they are primarily based on developed-country contexts and emphasize technological capabilities rather than organizational preparedness and user acceptance of change. This demonstrates a distinct gap in research, particularly regarding the adoption and operationalization of AI-based analytics (descriptive, diagnostic, ML, robotic process automation (RPA), NLP, and predictive analytics) in internal auditing functions in emerging markets. To fill this gap, the current research provides an empirical analysis of the influence of specific AI-based analytics on internal audit analytics in the Saudi private sector, providing context-specific evidence aligned with the digital transformation orientation of Saudi Arabia's Vision 2030 agenda.

2.1. Effect of descriptive and diagnostic analytics on internal audit analytics

Descriptive and diagnostic analytics significantly enhance internal audit analytics, playing a crucial role in preventing and detecting fraud. The independent supervisors of organizations are internal auditors, who are responsible for monitoring and examining their control systems to mitigate fraud-related threats, and such analytics tools are useful. Descriptive analytics enables auditors to observe historical trends and patterns that could be possible predictors of irregularities, and diagnostic analytics helps determine the reasons behind current issues, e.g., weaknesses of internal controls or policies that can be readily controlled. All these solutions will enhance auditors' ability to identify fraud and improve accountability within organizations (Anggraini et al., 2025). Data analytics may be more effective at delivering value-added internal audit results by reducing execution time and maximizing efficiency, effectiveness, and assurance relative to the audit sampling method. Detection rules are guidelines used in data analytics to detect anomalies in business transactions. Data analytics changes the paradigm of auditing, enables real-time analysis of transactions, provides continuous monitoring, and enhances the detection of anomalies (Usul and Alpay, 2025). Integrating diverse datasets such as financial, operational, and external data provides auditors with a comprehensive view of the organization's risk environment. Strict data governance procedures should be implemented to ensure data accuracy, consistency, and reliability. Furthermore, the use of ML methods and predictive analytics supports the identification of trends, emerging risks, and anomalies. Continuous monitoring with real-time data analytics can identify and respond in a timely manner to emerging threats (Ilori et al., 2024). Based on these insights, the first hypothesis is formulated as follows:

H1: Descriptive and diagnostic analytics have a positive impact on internal audit analytics.

2.2. Effect of ML on internal audit analytics

ML has transformed into a classic audit function. It optimizes audit functions by enabling the rapid processing and interpretation of high-speed, high-complexity data. ML algorithms can identify anomalies, assess risk, and generate automated reports more quickly and more precisely. Furthermore, ML-based auditing requires auditors to develop technical skills and operate in AI-supported environments (Bai, 2025). ML is an internal audit analytics tool used to improve risk assessment, detect fraud, and enhance operational efficiency. ML applications can analyze vast datasets to predict losses, identify anomalies, and strengthen internal controls. ML increases the speed and accuracy of internal audits. Furthermore, it raises important considerations around ethical use, data governance, and model transparency, as it transforms internal audit analytics into a more predictive and proactive function to improve risk management effectiveness. Based on these insights, the second hypothesis is formulated as follows:

H2: ML has a positive impact on internal audit analytics.

2.3. Effect of RPA on internal audit analytics

The automation of robotic processes improves internal auditing by reducing costs, eliminating human error, and streamlining workflows. The RPA system will enable sustained auditing, real-time risk management, and appropriate reporting; thus, it will alter the role of internal auditors and, in the long run, enhance organizational compliance and performance (Alassuli, 2025). RPA transforms internal audit analytics by improving compliance, streamlining processes, and enhancing audit quality. It enables the automation of tasks such as data extraction and report generation, allowing auditors to focus on fraud detection, risk assessment, and strategic decision-making. This shift increases accuracy, accelerates audit procedures, and supports real-time monitoring. Based on these insights, the third hypothesis is formulated as follows:

H3: RPA has a positive impact on internal audit analytics.

2.4. Effect of NLP and predictive analytics on internal audit analytics

Traditional audit practices often fall short in processing large and complex datasets. With the integration of AI, audits gain technological advantages that reduce audit duration, lower costs, and improve precision. Nonetheless, it is costly to develop, lacks sound rationale, requires qualified personnel, and threatens data integrity. Strengthening industry–academia–research collaboration, enhancing human–machine training, and improving data security can help mitigate these challenges. AI-driven audit transformation will overcome obstacles and facilitate the intelligent development of the audit industry (Shi, 2025). AI adoption can enhance the efficiency of internal audit analytics by moving beyond traditional tools such as Excel. Internal audits play a vital role in fraud detection and prevention, and this process can be enhanced through data analytics tools, such as Power BI, Tableau, and Python, to monitor transactions in real time, detect anomalies, and identify fraudulent activity. Thus, predictive analytics can uncover complex fraud patterns and anticipate risks (Thakkar et al., 2025). The application of AI tools in internal auditing represents a significant shift in auditing methods, particularly in fraud detection and process efficiency. By automating the analysis of large, complex financial datasets, NLP technologies supplement traditional auditing, enabling auditors to efficiently uncover anomalies, patterns, and signs of fraudulent activity. These technologies facilitate the auditing process and enhance auditors' ability to detect fraud. NLP also enhances the analysis and interpretation of textual financial statements, complementing the scope of audit analytics (Qatawneh, 2025). Based on these insights, the fourth hypothesis is formulated as follows:

H4: NLP and predictive analytics have a positive impact on internal audit analytics.

Despite the transformative potential of AI in internal auditing, the literature reveals several gaps. Prior studies suggest that technologies such as ML, NLP, or RPA can enhance fraud detection, compliance, and risk assessment. Nevertheless, studies indicate that AI is still underutilized in internal auditing procedures, particularly in Saudi Arabia's private sector, owing to high implementation costs, a lack of expertise, data security concerns, and resistance to change. Additionally, most of the literature focuses on economic environments in developed countries, which provides limited empirical evidence on the impact of AI on internal audit analytics in emerging economies, such as Saudi Arabia. It is also deficient in detailed frameworks that define how AI can effectively alter the approach, purpose, and level of assurance of internal audits, and address operational and ethical challenges. This highlights the need for context-based research to examine the opportunities and risks of AI adoption in internal auditing. Such research can provide empirical insights that support Saudi Arabia's Vision 2030 digital transformation strategy.

The basic assumption of the technology acceptance model is that it explains and predicts users' acceptance of technology. Perceived ease of use (PEOU) and perceived usefulness (PU) are the two primary constructs in the technology acceptance model (TAM) that determine technology adoption. PU denotes how effective the user believes a technology to be at improving the efficiency of a particular work. In contrast, PEOU refers to the ease with which a particular technology is used.

The TAM provides a conceptual framework for understanding the adoption of AI-based tools in internal audit analytics. The TAM posits that auditors tend to adopt analytical technologies when they perceive such technologies as applicable (PU) and easy to use (PEOU). Descriptive and diagnostic analytics enhance the comprehension of audit data and support decision-making in favor of H1, particularly regarding PU and PEOU. ML improves fraud detection and risk evaluation, supporting H2 by enhancing PU amid greater technical complexity. RPA also eases tedious audit processes and minimizes errors, supporting H3, given its PU and PEOU. Lastly, NLP and predictive analytics will enhance the processing of unstructured information and the proactive detection of risks, thereby supporting H4 by improving the effectiveness of audits and technology acceptance in the long term.

3. Field procedures

3.1. Methodology

The descriptive-analytical approach is defined by Aldosari (2020) as "a form of systematic scientific analysis and interpretation used to describe a specific phenomenon or problem and measure it by collecting standardized data and information about the phenomenon or problem, classifying, and analyzing it, and then carefully examining it." Given the substantial relevance of this approach, it was extensively employed in the present study.

3.2. Population and sample

The current study population comprises all internal audit employees in private companies in the Kingdom of Saudi Arabia, including internal audit managers, data analysis unit managers, and supervisors working in internal audit departments of registered private organizations. Due to the large size of the population, the sample included 384 members from the study population, selected through simple random sampling, according to Cochran's sample size formula, which is as follows:

$$n = \frac{Z^2 * P * (1-P)}{E^2} = \frac{(1.96)^2 * 0.5 * (1-0.5)}{(0.05)^2} = \frac{3.8416 * 0.25}{0.0025} = 384.16 \quad (1)$$

where, n is the required sample size; Z is the standard score (Z-score) corresponding to a 95% confidence level, which equals (1.96); P is the estimated proportion of a specific characteristic in the population, which equals (0.5); and E is the acceptable margin of error, which equals (0.05).

After distributing the questionnaire to the sample, the number of questionnaires valid for statistical analysis was 370, due to the retrieval of some questionnaires with incomplete responses or invalid for statistical analysis.

3.3. Sample characteristics

The demographic characteristics of the respondents, including gender, age, academic level, profession, and years of experience in auditing or accounting, were analyzed using descriptive statistics (frequencies and percentages), as presented in Table 1.

Table 1: Demographic characteristics of respondents

Variable	Category	Frequency	Percentage
Gender	Male	209	56.5%
	Female	161	43.5%
Age	Less than 20	45	12.2%
	20–29	57	15.4%
	30–39	103	27.8%
	40–49	94	25.4%
	More than 50	71	19.2%
Academic level	Secondary or less	57	15.4%
	High school diploma	74	20.0%
	Bachelor's	142	38.4%
	Graduate studies	97	26.2%
Profession	Internal auditing manager	67	18.1%
	Internal auditor	73	19.7%
	Auditing data analyst	60	16.2%
	Financial/accounting officer	76	20.5%
	Other	94	25.4%
Experience (years)	Less than 1 year	36	9.7%
	1–3 years	49	13.2%
	4–6 years	114	30.8%
	7–10 years	109	29.5%
	More than 10 years	62	16.8%

3.4. Instrument

The researcher developed a questionnaire to examine the role of AI and its influence on internal audit analytics in the Saudi private sector. To ensure validity and reliability, several procedures were followed. The questionnaire was first subjected to content validation by arbitrators, who reviewed its linguistic clarity, phrasing, and item appropriateness. Based on their feedback, some items were rephrased or removed, and the final version was approved by more than 83% of the reviewers. The finalized instrument consisted of 32 statements distributed across two axes. To further assess validity and reliability, the questionnaire was piloted with 30 participants.

3.4.1. First construct: AI adoption

The internal consistency of the first construct was assessed using Pearson correlation coefficients between individual items and their corresponding overall construct scores. The coefficients ranged from 0.675** to 0.898**, all statistically significant at the 0.01 level. Construct validity was further examined by calculating correlations between the dimension scores and the overall construct score, which ranged from 0.763** to 0.967**, all significant at the 0.01 level. Reliability was confirmed using Cronbach's alpha, with an overall coefficient of 0.940, indicating strong reliability and applicability.

3.4.2. Second construct: Internal audit analytics

Similarly, the internal consistency of the second construct was validated using Pearson correlation coefficients, which ranged from 0.734** to 0.887**, all statistically significant at the 0.01 level. Construct validity was confirmed through correlations between the dimension scores and the overall construct score, ranging from 0.822** to 0.927**, again significant at the 0.01 level. Cronbach's alpha reliability coefficient for this construct was 0.865, confirming reliability and the trustworthiness of the results.

The questionnaire employed a five-point Likert scale with the following response options: 1 = strongly disagree; 2 = disagree; 3 = somewhat agree; 4 = agree; 5 = strongly agree.

This study relies on perceptual data collected via a single questionnaire, which may introduce methodological bias due to reliance on a single instrument and data source and may affect the statistical relationships among the study variables. Therefore, to mitigate this bias, several preventive measures were implemented during instrument design, including emphasizing the confidentiality of information, anonymizing participants' identities, formulating statements clearly and neutrally, and distributing variable statements across different axes.

3.5. Statistical methods

The data was analyzed using SPSS software. The following statistical methods were applied: Pearson correlation coefficients, Cronbach's alpha, frequencies and percentages, arithmetic means and standard deviations, linear regression analysis, and the range equation. The response levels were categorized as very low (1), low (2), moderate (3), high (4), and very high (5). The class width for determining the verification degree of each dimension was calculated using the following formula:

$$\text{Class Width} = \frac{\text{Max. Limit} - \text{Min. Limit}}{\text{No. of Levels}} = \frac{5-1}{5} = 0.80 \quad (2)$$

4. Results

4.1. First construct: AI adoption

The arithmetic means and standard deviations of the first construct's dimensions (AI adoption) were calculated. Thereafter, these dimensions were ordered in descending order by their means, as shown in Table 2.

Table 2: Arithmetic means and standard deviation of the first construct's dimensions (AI adoption)

Dimensions	Mean	SD	Response degree	Rank
First dimension: Descriptive and diagnostic analytics	2.87	0.694	Moderate	3
Second dimension: ML	2.96	0.694	Moderate	1
Third dimension: RPA	2.79	0.710	Moderate	4
Fourth dimension: NLP and predictive analytics	2.92	0.701	Moderate	2
Overall mean	2.88	0.655	Moderate	

The data revealed that the overall mean for the first construct (AI adoption) was 2.88, with a standard deviation of 0.655, and a moderate response rate.

4.2. Second construct: Internal audit analytics

The arithmetic means and standard deviations of the dimensions of the second construct (internal audit analytics) were calculated. Thereafter, these dimensions were ordered in descending order by their means, as shown in Table 3. The data revealed that the second construct (internal audit analytics) had an arithmetic mean of 2.90 and a standard deviation of 0.689, indicating a moderate response rate.

4.3. Hypotheses

Descriptive and diagnostic analytics have a statistically significant impact on internal audit analytics ($\alpha \leq 0.05$). A simple linear regression analysis was employed to test this hypothesis, as presented in Table 4.

Table 3: Arithmetic means and standard deviation of the second construct's dimensions (internal audit analytics)

Dimensions	Mean	SD	Response degree	Rank
First dimension: Accuracy and reliability	2.94	0.704	Moderate	1
Second dimension: Efficiency	2.90	0.705	Moderate	2
Third dimension: Risk detection and fraud prevention	2.88	0.721	Moderate	3
Overall mean	2.90	0.689	Moderate	

The results indicate that descriptive and diagnostic analytics have a statistically significant impact on internal audit analytics. The R value was 0.906 at the 0.000 significance level, accounting for 82.1% of the variance in internal audit analytics (R^2 = 0.821). ML has a statistically significant impact on internal audit analytics ($\alpha \leq 0.05$). A simple linear regression analysis was employed, as shown in Table 5. The analysis showed that ML has a statistically significant impact on internal audit analytics. The R value was 0.931 at the 0.000 significance level, with ML accounting for 86.6% of the variance (R^2 = 0.866). RPA has a statistically significant impact ($\alpha \leq$ 0.05) on internal audit analytics. A simple linear regression analysis was conducted, as summarized in Table 6.

Table 4: Impact of descriptive and diagnostic analytics on internal audit analytics

Independent variable (IV)	B	Beta	R	R^2	T-value	Sig. T
Descriptive and diagnostic analytics	0.900	0.906	0.906[a]	0.821	41.044	0.000
Dependent variable (DV)	Internal audit analytics					
B_0: Intercept (constant)	0.324					
Adj R^2	0.820					
F-value	1684.575					
F-sig	0.000[b]					

a: Predictor: Descriptive and diagnostic analytics; b: $p < 0.001$ (statistically significant)

Table 5: ML impact on internal audit analytics

IV	B	Beta	R	R^2	T-value	Sig. T
ML	0.924	0.931	0.931[a]	0.866	48.854	0.000
DV	Internal audit analytics					
B_0: Intercept (constant)	0.169					
Adj R^2	0.866					
F-value	2386.717					
F-sig	0.000[b]					

a: Predictor: Machine learning (ML); b: $p < 0.001$ (statistically significant)

Table 6: RPA impact on internal audit analytics

IV	B	Beta	R	R^2	T-value	Sig. T
RPA	0.847	0.872	0.872[a]	0.760	34.109	0.000
DV	Internal audit analytics					
B_0: Intercept (constant)	0.543					
Adj R^2	0.759					
F-value	1163.455					
F-sig	0.000[b]					

a: Predictor: Robotic process automation (RPA); b: $p < 0.001$ (statistically significant)

The findings indicate that RPA has a statistically significant impact on internal audit analytics. The R value was 0.872 at the 0.000 significance level, with RPA accounting for 76.0% of the variance (R^2 = 0.760). NLP and predictive analytics have a statistically significant impact on internal audit analytics ($\alpha \leq 0.05$). A simple linear regression analysis was carried out, as shown in Table 7.

Table 7: Impact of NLP and predictive analytics on internal audit analytics

IV	B	Beta	R	R^2	T-value	Sig. T
NLP and predictive analytics	0.933	0.949	0.949[a]	0.900	57.455	0.000
DV	Internal audit analytics					
B_0: Intercept (constant)	0.175					
Adj R^2	0.899					
F-value	3301.067					
F-sig	0.000[b]					

a: Predictor: NLP and predictive analytics; b: $p < 0.001$ (statistically significant)

The results demonstrate that NLP and predictive analytics exert a statistically significant impact on internal audit analytics. The R value was 0.949[a] at a significance level of 0.000[b], accounting for 90.0% of the variance ($R^2 = 0.900$).

5. Discussion

The results of this study indicate that the adoption of AI technologies significantly enhances internal auditing. Among the examined tools, ML and predictive analytics demonstrated the most significant impact, as they provide in-depth insights and forward-looking capabilities. By contrast, procedural tools such as RPA yielded relatively lower results, reflecting their focus on operational efficiency rather than strategic value. This variance suggests that the true benefit of AI in internal auditing lies in integrating multiple tools, transforming the function from a traditional, compliance-oriented activity into a proactive, strategic mechanism that strengthens governance and improves risk management.

The literature indicates that ML and predictive analysis provide deep analytical insights and predictive capabilities that enable internal audit teams to improve risk prediction and enhance strategic decision-making, while routine automation instruments, such as RPA, focus on operational efficiency without adding significant strategic value (Shi, 2025; Alassuli, 2025). Studies have also confirmed that combining AI tools transforms the internal audit function from a traditional compliance role to a proactive, strategic one that enhances governance and improves risk management (Almahuzi, 2020; Popara et al., 2023).

The findings can be explained by AI's ability to integrate diverse analytical approaches, thereby improving audit procedures. Such integration enhances the accuracy of results and strengthens auditors' ability to process large volumes of data within a short timeframe. Furthermore, the use of multiple technologies provides a comprehensive view of financial and administrative processes within the organization, thus reducing the likelihood of human errors. Additionally, integrating descriptive, diagnostic, and predictive analytics enables audit teams to become more proactive, focusing on preventing risks rather than merely monitoring them after they occur.

The literature supports these findings, noting that the integration of AI technologies improves internal review procedures, increases the accuracy of results, and promotes reviewers' ability to process large volumes of data quickly and effectively (Anggraini et al., 2025). Studies indicate that integrating descriptive, diagnostic, and predictive analytics can enable audit teams to adopt a proactive approach that focuses on risk prevention rather than only monitoring risks after their occurrence (Usul and Alpay, 2025; Thakkar et al., 2025).

Descriptive and diagnostic analytics proved influential due to their ability to clarify historical trends and recurring patterns. This understanding helps auditors identify weaknesses and deviations directly, without relying solely on conventional auditing methods. Descriptive analytics generate precise quantitative indicators of past performance, while diagnostic analytics reveal the underlying causes of those results. This integration of description and explanation enhances the effectiveness of the auditing process and leads to more accurate and objective outcomes.

Studies indicate that descriptive and diagnostic analyses help auditors understand historical patterns and recurring deviations, enabling them to directly identify weaknesses without relying entirely on traditional approaches (Anggraini et al., 2025; Usul and Alpay, 2025). The literature shows that combining descriptive and diagnostic analyses enhances the efficiency of the review process and yields more precise and objective results (Ilori et al., 2024).

The increase in the proportion of the construed variance is attributable to AI algorithms' ability to detect hidden patterns in data. ML continuously improves models using new data, thereby enhancing their predictive performance. In turn, this strengthens the effectiveness of internal audits in identifying potential risks before their occurrence. Furthermore, the capacity to process large volumes of data rapidly, combined with the accuracy of extracting relevant relationships, increases the reliability of audit results and enhances their value to senior management.

The literature supports these findings, noting that ML algorithms enable the discovery of hidden patterns in data and continuously improve predictive performance as models are updated (Bai, 2025). Studies indicated that the ability to process large amounts of data quickly and precisely contributes to the reliability of internal review results and enhances their value for senior management decision-making (Almahuzi, 2020; Popara et al., 2023).

In the case of RPA, its recognized impact, although less significant than that of other technologies, stems from its functional nature. RPA focuses on automating routine and repetitive tasks, such as data entry and report generation, thereby reducing human effort and saving time. However, it does not provide substantial analytical value in isolation; its primary contribution lies in improving operational efficiency. Therefore, its impact is clear in reducing errors and expediting procedures, but it does not reach the level of influence achieved by more sophisticated analytical tools.

The literature indicates that RPA focuses on automating routine and repetitive tasks, such as data entry and report generation, thereby reducing human effort and saving time (Alassuli, 2025). Nonetheless, its analytical capabilities are limited relative to more advanced tools, and its role is limited to enhancing operational efficiency and expediting procedures.

Predictive analytics and NLP, by contrast, exert a profound impact due to the futuristic vision they provide. Predictive analytics enables the estimation of future risks and their probabilities, enabling internal audit teams to anticipate and address challenges more proactively. NLP facilitates the analysis of unstructured text data and documents, thereby broadening the scope of information available for auditing. The integration of predictive analytics and text analysis significantly enhances the quality of results and improves the accuracy of the internal audit process.

The literature supports these findings, indicating that predictive analytics and NLP technologies provide audit teams with foresight to anticipate risks and assess their probabilities, enhancing their ability to proactively address challenges (Qatawneh, 2025; Shi, 2025; Thakkar et al., 2025). NLP also expands the range of available information by analyzing unstructured text data, enhancing the quality and accuracy of internal audit findings.

Overall, differences in impact across AI applications can be attributed to the nature and role of each tool in the audit process. ML and predictive analytics, which offer in-depth analytical and predictive capabilities, exhibit higher explained variance ratios because they add a qualitative dimension to the auditor's work. Conversely, tools that focus on descriptive analysis or operational automation, such as descriptive analytics or RPA, have relatively lower impacts, as they primarily address basic or routine tasks. This disparity underscores the importance of integrating diverse tools to achieve optimal effectiveness, as such integration combines operational efficiency, analytical accuracy, and proactive, forward-looking insights.

Studies affirm that the level of impact varies according to the nature and function of each tool; advanced tools such as ML and predictive analytics offer higher analytical and strategic value, while descriptive or operational tools such as descriptive analytics and RPA focus on routine tasks (Almahuzi, 2020; Popara et al., 2023; Anggraini et al., 2025). This highlights the importance of integrating diverse tools to achieve maximum efficiency, as integration combines operational efficiency, analytical accuracy, and proactive insight.

6. Conclusion

The results of this study reveal that the adoption of AI technologies plays a significant role in enhancing internal auditing processes in Saudi private-sector companies. The findings indicate that all elements—descriptive analytics, diagnostic analytics, ML, RPA, predictive analytics, and NLP—substantially affect internal auditing. However, the degree of impact varies depending on the nature of the tool. Advanced analytical tools, such as ML and predictive analytics, demonstrate strong potential for explaining discrepancies and enhancing the proactive aspect of auditing, whereas other tools, such as descriptive analytics, diagnostic analytics, and process automation, primarily contribute to improving efficiency, accelerating processes, and reducing errors. Therefore, the key benefit of AI in internal auditing lies in integrating these diverse tools to ensure accuracy and reinforce reliability, efficiency, and proactive capabilities.

Based on these findings, the study suggests that companies increase investments in AI technologies and integrate them into their internal audit strategies. It further calls for specialized training programs to enhance auditors' skills in applying advanced analytical tools. Furthermore, it advocates strengthening digital governance practices by establishing effective data management systems and ensuring the quality of data input, thereby reducing risks associated with bias and algorithmic errors. Moreover, integrating automation with advanced analytical tools can maximize benefits and foster interdepartmental cooperation, creating a digital work environment that supports internal auditing activities.

Despite the importance of the findings of this study, it includes several methodological limitations that should be considered when interpreting the results:

- The study relied on a cross-sectional research design, where data were collected at a single point in time, which limits the ability to infer causal relationships or track changes in the effect of AI adoption on internal audit analyses over time.
- The study relied on self-perceptual data collected through a questionnaire, which may lead to some forms of bias, such as social bias, common method bias, and subjective interpretation of responses by respondents. Despite precautions taken during instrument design, this type of bias cannot be completely ruled out.
- The study was limited to a quantitative approach without the use of qualitative approaches, which limited the possibility of gaining a deeper understanding of the organizational and practical context of the use of AI technologies in internal audit work. Additionally, the absence of interviews or case studies prevented the study from exploring auditors' practical experiences and the challenges of applying these technologies.

- The study focused on a sample of internal auditors in the private sector in Saudi Arabia, which may limit the probability of generalizing the results to government sectors or different regulatory and legislative environments.

The study recommends that future research uses longitudinal designs to track the evolution of $AI's$ effects on internal audit analytics over multiple periods, enabling a deeper understanding of the causal relationships and dynamic changes resulting from rapid technological advances.

The study also recommends adopting a mixed-methods approach that combines quantitative and qualitative methods, integrating surveys with in-depth interviews or case studies, providing a more comprehensive understanding of internal auditors' experiences, organizational and technical challenges, and the maturity level of AI implementation within the organization.

Future studies should expand the scope of research to include different economic sectors within the kingdom or conduct comparative studies between the public and private sectors, thereby enhancing the generalizability of the results and supporting decision-makers in developing effective policies for adopting AI in internal auditing.

List of abbreviations

AI	Artificial intelligence
B	Unstandardized regression coefficient
Beta	Standardized regression coefficient
DV	Dependent variable
E	Margin of error
F-value	F-statistic value
IAFs	Internal audit functions
IV	Independent variable
ML	Machine learning
n	Sample size
NLP	Natural language processing
P	Estimated population proportion
PEOU	Perceived ease of use
PU	Perceived usefulness
R	Correlation coefficient
RPA	Robotic process automation
SD	Standard deviation
Sig.	Significance level (p-value)
T-value	T-statistic value
TAM	Technology acceptance model
Z	Standard score corresponding to confidence level

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Compliance with ethical standards

Ethical considerations

Participation was voluntary, and informed consent was obtained from all respondents. Anonymity and confidentiality were ensured, participants could withdraw at any time, and the data were used solely for this study.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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