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Original Research Article

Examining the Effects of Artificial Intelligence Dimensions on Internal Audit Quality: Evidence from Oman's Public Education Sector

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Abstract. The adoption of Artificial Intelligence (AI) is reshaping internal auditing practices within public-sector organizations facing heightened demands for transparency, accountability, and governance. Despite growing relevance, empirical evidence on how AI dimensions influence internal audit quality in public education institutions, especially in emerging economies such as Oman, remains limited. This study examines the effect of AI dimensions on internal audit quality in Oman's public education sector using a quantitative cross-sectional design. Data were collected from 240 internal auditors, financial controllers, and audit personnel at the General Directorate of Education in Al-Dakhiliyah. AI was operationalized across four dimensions; expert systems, neural networks, genetic algorithms, and intelligent agents, while internal audit quality was measured in terms of integrity, objectivity, competence, timeliness, and compliance with standards. The findings indicate that all four AI dimensions have statistically significant effects on internal audit quality, with genetic algorithms ($\beta = 0.456$, $p < 0.001$) emerging as the strongest predictor, followed by intelligent agents ($\beta = 0.288$, $p < 0.001$), neural networks ($\beta = 0.156$, $p = 0.002$), and expert systems ($\beta = 0.133$, $p < 0.001$). The model explains 78.4% of the variance in internal audit quality ($R^2 = 0.784$). These findings suggest that AI enhances audit effectiveness by improving analytical capacity, decision-making, and efficiency. Practically, the study highlights the need for public-sector institutions to invest in AI-enabled tools, auditor competencies, and data governance to strengthen audit quality. The study contributes empirical evidence from an emerging economy, supporting the Resource-Based View in explaining AI's role in improving audit performance.

Keywords Artificial intelligence; internal audit quality; public education sector; expert systems; Oman Vision 2040

Introduction

Digital technologies have changed the way public and private sector organizations manage operations, process information, and monitor institutional performance. In accounting and auditing, one of the technologies receiving increasing attention is artificial intelligence (AI). AI is being used to support routine automation, large-scale data processing, anomaly detection, and audit-related decision support (Appelbaum et al., 2018; Eulerich et al., 2023; Vasarhelyi et al., 2012). These developments suggest that internal auditing is no longer limited to conventional compliance checking. It is increasingly expected to contribute to internal control, risk management, accountability, and organizational improvement through more systematic use of digital tools.

Internal auditing is particularly important in the public sector because public agencies are required to safeguard public resources, comply with regulations, and demonstrate accountability to citizens and oversight bodies. In this setting, internal auditors are expected to assess not only financial compliance, but also risk management practices, control systems, operational procedures, and the reliability of institutional reporting. Professional bodies have also acknowledged that emerging technologies may assist auditors by improving access to audit evidence, reducing repetitive manual work, and supporting more timely audit procedures

(Institute of Internal Auditors [IIA] 2024; International Auditing and Assurance Standards Board [IAASB], 2021). AI applications such as expert systems, neural networks, genetic algorithms, and intelligent agents may help auditors analyse complex datasets, identify unusual patterns, and prioritise audit attention. However, these tools do not remove the need for professional judgement, ethical awareness, and proper governance of audit processes.

In Oman, the relevance of AI-enabled auditing needs to be understood within the broader national agenda of digital transformation. Oman Vision 2040 places emphasis on the modernization of public administration, institutional efficiency, and improved governance through the use of technology (Government of Oman, 2021). Public institutions, including those in the education sector, are therefore expected to improve administrative, financial, and monitoring systems. For the General Directorates of Education, internal audit units play an important role in supporting accountability, compliance, and resource management. Yet, the extent to which AI-related capabilities are associated with internal audit quality in this public education context remains underexplored.

Previous studies on AI in auditing have mainly examined private organizations, audit firms, and financial institutions, often in settings with more developed technological infrastructure (Issa et al., 2016; Rosli et al., 2012). Although these studies provide useful insights, their findings may not fully reflect the realities of public-sector education institutions, where audit functions are shaped by administrative procedures, public accountability requirements, and resource constraints. In addition, much of the existing literature discusses AI adoption in broad terms, with less attention to the specific dimensions of AI that may be relevant to audit quality. This creates a need for empirical evidence that distinguishes between different AI capabilities rather than treating AI as a single general construct.

This gap provides the basis for the present study, which examines the relationship between four AI dimensions and internal audit quality in Oman’s public education sector. The four dimensions are expert systems, neural networks, genetic algorithms, and intelligent agents. The study focuses on the General Directorate of Education in Al-Dakhiliyah Governorate. By examining these AI dimensions separately, the study seeks to provide a more specific understanding of how different AI-related capabilities are associated with internal audit quality. The findings may offer useful evidence for internal auditors, public-sector managers, policymakers, and education administrators who are considering how AI can be integrated into audit functions in a responsible and context-sensitive manner.

The conceptual logic of this study is based on the Resource-Based View (RBV), which suggests that organizational performance is influenced by how effectively resources are developed and utilized (Barney, 1991; Barney, 2001; Peteraf, 1993). From this perspective, resources that are valuable and appropriately organized may contribute to improved organizational processes and outcomes. In the context of auditing, artificial intelligence (AI) can be considered not only as a technical tool but also as a resource that may support audit-related activities. These activities include audit planning, evidence analysis, anomaly detection, and monitoring processes. However, prior studies note that the presence of digital tools alone does not guarantee improved performance, as their effectiveness depends on how they are integrated into existing practices and supported by organizational capabilities (Kokina & Davenport, 2017; Vasarhelyi et al., 2015).

Accordingly, the present study considers AI as a multidimensional construct that may be associated with internal audit quality. Rather than treating AI as a single concept, the study focuses on four specific dimensions: expert systems, neural networks, genetic algorithms, and intelligent agents. This approach is consistent with prior research, which suggests that different AI techniques serve different functional roles in audit processes (Issa et al., 2016; Brown-Liburd et al., 2015). By examining these dimensions separately, the study aims to provide a more specific understanding of how particular AI capabilities may relate to audit tasks such as risk assessment, evidence evaluation, and decision support. This distinction is important, as the contribution of AI to audit work may vary depending on the type of technology used and the context in which it is applied (Yoon et al., 2015).

Expert systems are commonly described as rule-based systems that rely on predefined knowledge structures to support decision-making. In auditing, such systems may assist in applying established procedures and compliance criteria in a more consistent manner (Issa et al., 2016; Kokina & Davenport, 2017). This may be particularly relevant in public-sector settings, where audit tasks often involve recurring regulatory requirements. By supporting structured decision processes, expert systems may help reduce variability in audit judgments and support adherence to established standards. However, their effectiveness depends on the quality and relevance of the embedded rules. Based on these considerations, expert systems are expected to be positively related to internal audit quality.

Neural networks are associated with the ability to process large volumes of data and identify patterns that may not be easily detected using traditional analytical methods. In audit contexts, this capability has been discussed in relation to anomaly detection, fraud risk identification, and data analysis (Brown-Liburd et al., 2015; Yoon et al., 2015). These features may support auditors in identifying unusual transactions and improving the timeliness of audit procedures. Previous studies highlight that the usefulness of such models depends on data quality and the ability to interpret model outputs (Appelbaum et al., 2017). Considering these factors, neural networks are expected to be positively related to internal audit quality.

Genetic algorithms are typically used for optimisation problems and may be applied in audit settings to support planning and resource allocation decisions. In environments where audit units must manage multiple responsibilities with limited resources, optimisation techniques may assist in prioritising higher-risk areas and structuring audit activities more efficiently (Vasarhelyi et al., 2015; Appelbaum et al., 2017). This may be particularly relevant in public-sector audit contexts, where coverage requirements are broad and resource constraints are common. However, the effectiveness of these techniques depends on the appropriateness of the underlying assumptions and input data. On this basis, genetic algorithms are expected to be positively related to internal audit quality.

Intelligent agents are systems that can perform automated tasks such as monitoring, alert generation, and exception identification. In auditing, these systems have been discussed in relation to continuous auditing and real-time oversight (Alles et al., 2006; Issa et al., 2016). Such capabilities may support ongoing monitoring of transactions and help auditors respond more quickly to potential issues. This may be particularly useful in environments with high volumes of routine transactions, where manual monitoring is difficult to sustain. However, their effectiveness depends on system design and appropriate oversight mechanisms. Accordingly, intelligent agents are expected to be positively related to internal audit quality.

Overall, the introduction develops the argument that different AI dimensions may be associated with internal audit processes and, in turn, with internal audit quality. The study does not assume direct causality but instead examines whether statistically significant relationships exist between these variables. Based on this theoretical and empirical logic, four hypotheses are proposed: H1, expert systems are positively related to internal audit quality; H2, neural networks are positively related to internal audit quality; H3, genetic algorithms are positively related to internal audit quality; and H4, intelligent agents are positively related to internal audit quality.

Methodology

This study used a quantitative cross-sectional survey design to examine whether different dimensions of artificial intelligence (AI) adoption predict internal audit quality in Oman’s public education sector. This design was appropriate because the study required numerical data that could capture respondents’ perceptions of AI utilisation and internal audit quality at a particular point in time. Since the data were collected once and no intervention was introduced, the analysis was limited to statistical prediction and association. Therefore, the findings should not be interpreted as evidence of causal effects.

Data were collected through a structured self-administered questionnaire. A survey approach was suitable for this study because it enabled the researchers to obtain standardised responses from employees involved in audit-related, financial, and technology-based functions within the selected public education institution. The questionnaire was administered through both face-to-face and online modes. This approach was adopted to increase response coverage, as some respondents were more accessible through direct distribution, while others preferred to complete the questionnaire electronically because of work schedules and departmental arrangements.

The population of the study consisted of approximately 745 employees from the accounting, auditing, financial control, and information technology departments at the General Directorate of Education in Al-Dakhiliyah Governorate, Oman. These groups were selected because their roles were connected to financial monitoring, audit processes, digital systems, and administrative accountability. A simple random sampling technique was applied using the official employee list as the sampling frame. Each eligible employee was assigned a number, after which a random number generator was used to select respondents. This procedure was intended to reduce selection bias and provide each eligible employee with an equal chance of inclusion. Out of 250 questionnaires distributed, 240 were completed and usable for analysis.

The data collection process began after permission had been obtained from the relevant authority at the General Directorate of Education in Al-Dakhiliyah Governorate. The questionnaires were distributed through official communication channels as well as direct contact with selected respondents. Before answering the questionnaire, respondents were informed about the purpose of the study, the voluntary nature of their participation, and the estimated completion time. Each questionnaire required approximately 10 to 15 minutes to complete. Data collection took place over four weeks. Returned questionnaires were checked for completeness, and responses with substantial missing information were excluded before the final dataset was prepared.

The questionnaire was adapted from previous studies on AI in auditing and internal audit quality, particularly Issa et al. (2016), Kokina and Davenport (2017), and Alzeban and Gwilliam (2014). Some items were refined to ensure their relevance to the public-sector education context in Oman. The instrument contained two main sections. The first section measured AI utilisation through four dimensions: expert systems, neural networks, genetic algorithms, and intelligent agents. This section consisted of 22 items. The second section measured internal audit quality using 15 items related to integrity, objectivity, competence, timeliness, and compliance with professional standards. All items were measured on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree.

To improve the suitability of the instrument, face validity was assessed by academics with expertise in accounting and auditing. Their comments were used to revise item wording, improve clarity, and ensure closer alignment between the questionnaire and the study objectives. Reliability was then examined using Cronbach's Alpha. The coefficients ranged from 0.710 to 0.937 across the study constructs, indicating acceptable to high internal consistency. These results suggest that the adapted questionnaire had sufficient reliability for measuring AI utilisation and internal audit quality in the present study.

Ethical procedures were followed throughout the research process. Approval to conduct the study was obtained before data collection. Respondents were informed that participation was voluntary and that they could decline to participate without consequence. Informed consent was obtained before the questionnaire was completed. No personally identifiable information was reported in the study, and responses were treated confidentially. These measures were taken to protect respondents' privacy and to ensure that the data were used only for academic research purposes.

The data were analysed using SPSS. Descriptive statistics, including means and standard deviations, were used to describe the levels of AI utilisation and internal audit quality. Multiple regression analysis was conducted to test the proposed hypotheses and to examine the predictive relationship between the four AI dimensions and internal audit quality. The analysis considered regression coefficients, t-values, F-statistics, and the coefficient of determination. Statistical significance was assessed at the 0.05 level. Given the cross-sectional nature of the study, the regression results were interpreted as evidence of statistical prediction rather than causality.

The Findings

The findings are organised into three components: the demographic profile of respondents, descriptive statistics, and regression analysis. A total of 240 valid responses were obtained from internal auditors, financial controllers, and audit personnel within the General Directorate of Education in the Al-Dakhiliyah Governorate, Sultanate of Oman. The composition of respondents is particularly relevant for this study, as these roles are directly involved in audit processes and are increasingly exposed to technology-driven practices. The sample is largely dominated by male respondents, with most participants aged between 30 and 49 years. This age distribution reflects a workforce situated within the mid-career stage, where professional experience is relatively established while still maintaining adaptability to emerging technologies. In terms of educational attainment, the majority hold at least a bachelor's degree, indicating a level of formal training that supports engagement with data-driven and AI-assisted audit environments.

In addition, more than half of the respondents reported over ten years of working experience, suggesting a depth of practical exposure to audit procedures and organisational systems. Such experience is particularly important when evaluating perceptions of AI utilisation, as it allows respondents to make comparisons between conventional and technology-enabled audit practices. Respondents were drawn from financial, performance, and compliance audit functions, with financial audit representing the largest proportion. This distribution reflects the operational emphasis within the organisation and provides a meaningful basis for interpreting subsequent statistical analyses in relation to internal audit quality.

Descriptive analysis

The descriptive analysis focuses on the level of Artificial Intelligence (AI) utilisation in internal auditing and its alignment with the requirements of high-quality audit practices in the public sector. Given the increasing integration of digital technologies in organisational processes, examining these patterns provides an initial indication of how far AI has been incorporated into audit functions. The results show that AI utilisation is at a moderate to moderately high level, whereas internal audit quality is rated high. This suggests that although AI tools are already being used across audit activities, their integration may not yet be fully optimised. Table 1 presents the mean scores and standard deviations for each construct.

Table 1. Descriptive Statistics for Main Constructs

Construct	**Dimension**	**Mean (M)**	**Std. Deviation (SD)**	**Interpretation**
Artificial Intelligence (IV)	Expert Systems	3.56	0.46	Moderate
	Neural Networks	3.57	0.52	Moderate
	Genetic Algorithms	3.66	0.61	High
	Intelligent Agents	3.64	0.46	Moderate–High
Overall Artificial Intelligence	—	3.61	0.51	Moderate–High
Internal Audit Quality (DV)	—	4.07	0.33	High

Table 1 presents the descriptive statistics for the main constructs examined in this study. The results indicate that the utilisation of Artificial Intelligence (AI) across the four dimensions ranges from moderate to moderately high, suggesting that AI tools have been introduced into internal audit practices but are not yet fully integrated into routine operations. Among the dimensions, genetic algorithms recorded the highest mean score, pointing to a stronger perceived relevance of optimisation-based techniques within the audit context. Intelligent agents also showed relatively higher usage compared to expert systems and neural networks. In contrast, internal audit quality was rated at a high level, indicating that audit practices are generally perceived to be effective within the organisation. This contrast between the relatively strong audit quality and the more moderate level of AI utilisation suggests that current audit performance is still largely supported by conventional practices, with AI playing a complementary rather than central role. These observations provide a basis for further analysis of how each AI dimension contributes to the prediction of internal audit quality.

Multiple Regression Analysis and Hypotheses Testing

Prior to the regression analysis, diagnostic tests were performed to ensure that the underlying assumptions were met. The results indicated no major issues, particularly with respect to multicollinearity, as all variance inflation factor (VIF) values fell within acceptable thresholds. Multiple regression analysis was then employed to assess the extent to which the four Artificial Intelligence (AI) dimensions—expert systems, neural networks, genetic algorithms, and intelligent agents—predict internal audit quality. The overall model was statistically significant, with $R^2 = 0.784$ and adjusted $R^2 = 0.780$, indicating that the predictors collectively explain a substantial proportion of the variance in audit quality. The model also demonstrated a strong fit, $F(4, 235) = 213.428$, $p < 0.001$ ($N = 240$). Detailed regression coefficients are reported in Table 2.

Table 2. Multiple Regression Results Predicting Internal Audit Quality

Predictor	B	SE	β	t	p
Constant (Intercept)	1.738	0.090	—	19.286	<0.001
Expert Systems	0.096	0.027	0.133	3.610	<0.001
Neural Networks	0.105	0.034	0.156	3.064	0.002
Intelligent Agents	0.197	0.037	0.288	5.347	<0.001
Genetic Algorithms	0.247	0.023	0.456	10.961	<0.001

The regression results, as presented in Table 2, indicate that all four AI dimensions have a statistically significant relationship with internal audit quality. Among these, genetic algorithms show the strongest predictive contribution, followed by intelligent agents, neural networks, and expert systems. This ordering suggests that AI capabilities associated with optimisation and automated decision processes are more influential within the audit environment. Such findings may reflect the increasing reliance on data-driven techniques in audit tasks, particularly in areas requiring efficiency, pattern optimisation, and large-scale data processing. In comparison, rule-based systems and traditional pattern-recognition approaches appear to play a relatively smaller role. Overall, the results provide empirical support for all proposed hypotheses, confirming the relevance of each AI dimension in explaining variations in internal audit quality.

Discussion

This study examined whether expert systems, neural networks, genetic algorithms, and intelligent agents predict internal audit quality in Oman's public education sector. The results show that all four AI dimensions were statistically significant predictors of perceived internal audit quality. Among them, genetic algorithms recorded the strongest relative association, followed by intelligent agents, neural networks, and expert systems. Since the study used a cross-sectional survey design, these findings should be interpreted as evidence of statistical prediction rather than causal effect. Nevertheless, the results suggest that different AI capabilities may be associated with different aspects of internal audit quality in a public-sector education setting.

The findings can be interpreted through the Resource-Based View (RBV), which explains organizational performance in relation to how institutions develop and use valuable internal resources (Barney, 1991). In the context of this study, AI is not viewed merely as a technical tool, but as a set of organizational capabilities that may support audit planning, evidence analysis, risk prioritisation, anomaly detection, and audit monitoring. Expert systems, neural networks, genetic algorithms, and intelligent agents therefore become useful when they are integrated into audit routines, supported by reliable data, and used by auditors who possess both technical and professional competence. This interpretation is consistent with recent discussions by (Gu et al., 2024; Leocádio et al., 2024), who argue that AI contributes to auditing when it is embedded within institutional processes and professional judgement rather than treated as a stand-alone technological solution.

The findings should also be read in relation to the concept of internal audit quality. Internal audit quality is not limited to the completion of audit assignments or the production of audit reports. It is closely related to integrity, objectivity, competence, timeliness, and compliance with professional standards, as emphasized in the (IIA, 2024). In the public sector, these dimensions are particularly important because internal audit units are expected to support accountability, risk management, internal control, and responsible use of public resources. The relatively high level of perceived internal audit quality in this study suggests that respondents evaluated the audit function within the General Directorate of Education positively in terms of professional quality. At the same time, the regression results indicate that AI-related capabilities are associated with this perceived quality, particularly through their support for analytical work, monitoring, and structured decision-making.

Expert systems were positively and significantly associated with internal audit quality, although their relative association was the weakest among the four AI dimensions. This may be explained by the rule-based nature of expert systems. In internal auditing, expert systems can assist auditors in applying audit procedures, compliance rules, and professional criteria in a more consistent manner. (Issa et al., 2016) note that AI has potential to formalize audit tasks and support audit judgement, while (Kokina & Davenport, 2017) show that automation can reshape audit work by reducing repetitive tasks and supporting professional decision-making. Such capability is relevant in public-sector settings, where audit work often involves recurring administrative, financial, and regulatory requirements. However, the smaller relative association in this study suggests that rule-based systems may be less influential than AI applications that support more complex analytical or optimisation tasks. This also indicates that expert systems remain useful, but their contribution depends on professional interpretation and contextual assessment by auditors.

Neural networks were also found to be a significant predictor of internal audit quality. This suggests that pattern-recognition capability may be relevant to audit work, especially where auditors need to identify unusual transactions, hidden patterns, or potential risk signals in large datasets. Neural networks may support audit quality by improving auditors' ability to detect anomalies and examine relationships that are not easily visible through conventional audit procedures. (Brown-Liburd et al., 2015) discuss how data analytics may affect audit judgement, while (Yoon et al., 2015) explain the role of big data as complementary audit evidence. However, the contribution of neural networks should be interpreted carefully. These systems require good-quality data, technical expertise, model validation, and mechanisms for explaining results. Without such conditions, their outputs may be difficult for auditors to interpret or defend.

Genetic algorithms recorded the strongest relative association with internal audit quality. This finding indicates that optimisation-related AI capabilities may be particularly relevant in the context of public education administration. Internal audit units in this setting often need to allocate limited audit resources across departments, financial processes, procurement activities, compliance areas, and risk categories. Genetic algorithms may support audit planning by helping auditors identify more efficient combinations of audit coverage, risk prioritisation, and resource allocation. From an RBV perspective, this suggests that optimisation capability may function as a valuable organizational resource when it supports better audit planning and more targeted use of audit capacity (Barney, 1991). Nevertheless, this result should not be read as evidence that genetic algorithms automatically improve audit quality. Their usefulness depends on the quality of input data, the suitability of optimisation criteria, and the ability of auditors to evaluate algorithmic recommendations critically.

Intelligent agents also showed a strong positive relationship with internal audit quality. This may reflect their relevance to monitoring, automated alerts, exception reporting, and follow-up activities. In internal auditing, timeliness is an important quality dimension because delayed detection of irregularities can reduce the usefulness of audit findings. Intelligent agents may help audit units identify issues earlier and improve audit responsiveness, especially in environments involving large volumes of routine transactions. This finding is consistent with the broader literature on continuous auditing and technology-supported audit monitoring, which suggests that digital tools can extend audit coverage and support more timely assurance (Vasarhelyi et al., 2012; Appelbaum et al., 2018). At the same time, automated alerts should not be accepted without professional review. Auditors must verify whether flagged exceptions are meaningful within the operational context.

Taken together, the findings show that AI should not be treated as a single, uniform construct in auditing research. Each AI dimension appears to support a different aspect of audit work. Expert systems are more closely related to structured reasoning and procedural consistency. Neural networks are associated with pattern recognition and anomaly detection. Genetic algorithms are linked to optimisation, audit planning, and risk prioritisation. Intelligent agents support monitoring and responsiveness. This multidimensional interpretation adds specificity to the discussion of AI-enabled auditing by showing that different AI capabilities may relate to different mechanisms of internal audit quality.

The findings are broadly in line with studies suggesting that AI and audit analytics may support audit efficiency, audit evidence evaluation, risk assessment, and decision-making (Brown-Liburd et al., 2015; Yoon et al., 2015; Gu et al., 2024). However, the literature is not entirely consistent. Some studies report positive relationships between AI adoption and audit outcomes, while others emphasize barriers such as limited digital skills, weak infrastructure, poor data quality, privacy concerns, cybersecurity risks, and lack of trust in AI-generated outputs (Afsay et al., 2023; Leocádio et al., 2024). The present findings should therefore be understood within this mixed evidence base. The positive statistical relationships observed in this study may reflect respondents' perceptions of the usefulness of AI capabilities, but the actual contribution of AI to audit quality depends on implementation conditions, institutional support, and the maturity of audit data systems.

The public-sector education context gives the findings additional significance. Public education institutions are responsible for managing public funds, procurement processes, administrative operations, and compliance requirements across multiple units. These conditions differ from those of private firms, external audit practices, or financial institutions, which have been more widely examined in previous studies. In Oman, the findings are also relevant to the broader direction of Oman Vision 2040, which emphasizes digital transformation, governance modernization, and public-sector efficiency (Government of Oman, 2021). AI-related audit capabilities may support this agenda if they are introduced as part of a broader governance framework rather than as isolated technical applications.

The study also highlights the continuing importance of professional judgement in AI-enabled auditing. AI may support audit work by improving data processing, risk identification, monitoring, and planning. However, internal audit quality still depends on auditors' integrity, objectivity, competence, and adherence to professional standards, as emphasized in the (IIA, 2024). This means that AI should be viewed as a supporting capability rather than a substitute for professional audit judgement. Auditors remain responsible for interpreting AI outputs, questioning automated recommendations, documenting audit reasoning, and ensuring that conclusions are defensible. (Gu et al., 2024) and (Rahman et al., 2024) similarly emphasize the need for explainability, human oversight, and accountability in AI-supported audit environments.

From a theoretical standpoint, the study extends RBV by showing how different AI dimensions can be conceptualised as audit-related organizational capabilities. The findings suggest that not all AI resources are equally associated with internal audit quality. In this context, optimisation and monitoring capabilities appear to have stronger relative associations than rule-based or pattern-recognition capabilities. This provides a more specific application of RBV in internal auditing by linking particular technological resources to audit quality outcomes. The study also contributes to internal audit quality literature by showing that technology-enabled capabilities need to be assessed in relation to professional quality dimensions such as timeliness, competence, objectivity, and compliance with standards.

The practical implications are also important. Public education institutions should approach AI adoption in internal auditing as a planned governance initiative rather than as a general technological upgrade. Priority may be given to AI tools that support risk-based planning, exception detection, continuous monitoring, and evidence-based decision-making. Internal auditors also need training in data analytics, AI interpretation, algorithmic limitations, and validation of automated outputs. For public-sector managers, the findings point to the need for data governance policies, secure digital infrastructure, and coordination between audit, finance, and information technology units. Policymakers may also consider developing clearer guidelines on transparency, accountability, data privacy, cybersecurity, and human oversight in AI-supported auditing.

Overall, the findings suggest that AI-related capabilities are meaningfully associated with perceived internal audit quality in Oman's public education sector. However, their value depends on the way they are governed, interpreted, and integrated into audit practice. The results support a cautious but constructive view of AI in internal auditing. AI may support perceived audit quality when it improves analytical capacity, planning, monitoring, and responsiveness, provided that these capabilities remain under professional and institutional control.

Conclusion

This study examined the predictive relationship between four artificial intelligence (AI) dimensions and internal audit quality in Oman's public education sector. The dimensions examined were expert systems, neural networks, genetic algorithms, and intelligent agents. The findings showed that all four dimensions were significantly associated with perceived internal audit quality, with genetic algorithms recording the strongest relative association, followed by intelligent agents, neural networks, and expert systems. These results suggest that AI-related capabilities may be relevant to audit planning, monitoring, anomaly detection, risk prioritisation, and evidence-based audit work. However, since the study used a cross-sectional survey design, the findings should be interpreted as evidence of statistical association and prediction rather than causal effect.

The study contributes to the literature by examining AI-enabled auditing in a public-sector education setting that has received limited empirical attention. Much of the existing research has focused on audit firms, financial institutions, private organizations, or developed technological environments. By focusing on the General Directorate of Education in Al-Dakhiliyah Governorate, this study extends the discussion to a public education context where accountability, compliance, resource management, and administrative control are central to audit work. The study also contributes to the Resource-Based View by treating AI not as a single technological construct, but as a set of organizational capabilities. This distinction is important because expert systems, neural networks, genetic algorithms, and intelligent agents may support different aspects of internal audit quality. The study therefore offers a more specific understanding of how AI-related resources are associated with professional audit dimensions such as integrity, objectivity, competence, timeliness, and compliance with standards.

The findings have practical implications for public education institutions, internal auditors, public-sector managers, and policymakers. For educational institutions, AI adoption in internal auditing should be planned as part of a broader governance initiative rather than introduced as a general technological upgrade. Priority may be given to AI applications that support risk-based planning, exception detection, continuous monitoring, and evidence-based audit decisions. Internal auditors need appropriate training in data analytics, interpretation of AI outputs, algorithmic limitations, and validation of automated recommendations. Public-sector managers should also strengthen data governance, digital infrastructure, cybersecurity controls, and coordination between audit, finance, and information technology units. For policymakers, the findings point to the need for clearer guidelines on transparency, accountability, privacy protection, and human oversight in AI-supported auditing, particularly in line with Oman's wider digital transformation agenda under Oman Vision 2040.

Several limitations should be acknowledged. First, the study used a cross-sectional survey design, which means that the results cannot establish causal relationships between AI dimensions and internal audit quality. Future research may use longitudinal designs to examine how AI-supported auditing develops over time. Second, the study focused on one public education directorate in Al-Dakhiliyah Governorate, which may limit the generalisability of the findings to other governorates, ministries, or private-sector organizations. Future studies could compare different public-sector institutions or include wider regional samples. Third, the data were based on self-reported perceptions, which may involve perceptual bias or common method bias. Although the study used expert review and reliability testing to improve the quality of the instrument, future research may combine survey data with interviews, audit documents, system logs, or objective audit performance indicators. Such approaches would provide a more comprehensive understanding of how AI capabilities are used in actual internal audit practice.

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