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# The Impact of Artificial Intelligence on the Audit Process and Internal Audit Quality: A Study of Listed Companies on the Vietnamese Stock Market

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**ABSTRACT**

In the context of the Fourth Industrial Revolution, adopting artificial intelligence (AI) in internal auditing has become an essential trend to enhance the efficiency and accuracy of audit processes. As corporate information systems grow increasingly complex, AI provides critical support in optimizing audit procedures by enabling automated data processing, advanced risk detection, and more comprehensive analyses. This study investigates the key factors influencing AI adoption in internal audit functions among companies listed on the Vietnamese stock market. Using structural equation modeling (SEM), the analysis reveals that internal auditors' technological competency, managerial support, organizational culture, and information technology infrastructure all have a significant positive impact on AI adoption. Furthermore, the study examines the relationship between AI adoption, audit process effectiveness, and internal audit quality. The results indicate that higher levels of AI integration improve audit process efficiency by reducing manual workloads, minimizing errors, and enhancing the detection of risks and anomalies. Importantly, improvements in audit processes serve as a crucial mediating mechanism through which AI adoption contributes to overall internal audit quality. These findings underscore the strategic importance of integrating AI within well-structured audit procedures and highlight the need for organizations to invest in technology, training, and supportive organizational practices to fully realize the benefits of AI in internal auditing.

**Keywords:** artificial intelligence, audit process, audit quality, internal audit, listed companies.

## INTRODUCTION

In the context of rapid digital transformation, the Fourth Industrial Revolution has opened opportunities for enterprises to access and apply advanced technologies such as artificial intelligence (AI), blockchain, and big data analytics. AI has increasingly established itself as a powerful tool to assist managers in enhancing risk identification, optimizing business operations, and improving management efficiency. The automation of processes and fraud detection through AI-driven data analysis enhances the effectiveness of auditing activities in terms of analysis and prediction (Cristea, 2020). By leveraging computer programs to quickly process large volumes of data, AI significantly reduces auditing time and allows auditors to focus more on procedures in high-risk areas. Moreover, AI can assess massive datasets rapidly and accurately while providing superior analytical capabilities to detect unusual transactions and minimize human errors. Consequently, audit quality is substantially improved (Anastassia et al., 2022).

AI opens up new opportunities to enhance the efficiency and value of auditing activities, particularly internal auditing. Internal audit functions ensure legal compliance, timely financial reporting, and provide tools to improve operational effectiveness (Jiang et al., 2020). It serves not only as a financial oversight mechanism but also as a unit

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that ensures the effectiveness and efficiency of control procedures and risk management. AI is considered a strategic tool that enables internal audit departments to transform from traditional models to intelligent auditing, aiming for more proactive and transparent risk governance. AI can assist auditors in identifying patterns, trends, and anomalies within financial data. Consequently, internal auditors can conduct in-depth analyses and comprehensive assessments, allowing them to deliver valuable conclusions in a timely manner.

Nonetheless, for the effective implementation of AI, auditors must possess a clear understanding of the technology's inherent limitations and view AI as an auxiliary instrument that complements, rather than supplants, their core professional competencies. As the capabilities of AI-driven auditing systems continue to evolve, it becomes imperative for internal auditors to strategically consider the integration of AI into audit processes in order to enhance the overall quality, rigor, and reliability of their work.

For listed companies on the Vietnamese stock market, the adoption of AI in internal auditing holds significant importance, as AI not only affects audit quality but also influences managerial decision-making processes. However, the implementation of AI in Vietnam still faces several challenges, including unstandardized data infrastructure, high investment costs, and a shortage of highly skilled personnel with advanced technological expertise. Therefore, examining the impact of AI on the internal audit function - particularly in terms of enhancing audit quality - represents a timely and relevant issue. This study focuses on analyzing the effects of AI on audit processes and internal audit quality in listed companies on the Vietnamese stock market, thereby providing practical recommendations for these enterprises to effectively leverage AI in order to improve internal audit quality.

## THEORETICAL FRAMEWORK

The Diffusion of Innovations theory was developed by Everett M. Rogers in 1962. Rogers investigated how new ideas, products, or processes are communicated and spread within a social system. According to this theory, the adoption of innovations does not occur uniformly but depends on several factors, including the characteristics of the innovation, communication channels, time, and the social system.

The Diffusion of Innovations theory explains the mechanisms, reasons, and speed at which a new idea, product, or technology spreads within a community or social system. Rogers divided the innovation adoption process into five main stages: knowledge, persuasion, decision, implementation, and confirmation. Each stage reflects the steps that individuals or organizations go through when encountering, evaluating, and applying a new idea or product. Simultaneously, he classified adopters into five categories based on their characteristics and behaviors during the diffusion process: innovators, early adopters, early majority, late majority, and laggards. Rogers' theory has provided a foundational framework for understanding technological change and the adoption of innovations in various fields.

The Diffusion of Innovations theory provides a useful framework for understanding how AI is adopted and implemented by enterprises. The theory highlights that the adoption of AI depends on multiple factors, such as its compatibility with existing processes, the ability to experiment and observe outcomes before widespread implementation, and the complexity involved in deployment. Additionally, the theory enables the classification of different adopter groups, which can inform the development of targeted and effective AI implementation strategies for each group.

The Technology Acceptance Model (TAM) examines the factors that influence an individual's acceptance and use of new technologies (Davis, 1989). This model provides a foundation for analyzing auditors' attitudes, perceptions, and readiness to integrate AI into auditing processes. Personal competence and technological proficiency play crucial roles in the adoption and application of new technologies. Key constructs of TAM, particularly perceived ease of use and perceived usefulness, have been consistently identified in research as critical factors shaping auditors' attitudes and intentions toward adopting new technologies, thereby contributing to the enhancement of audit quality.

According to the Resource-Based View (RBV), a firm's internal resources and capabilities are key determinants for creating sustainable competitive advantage (Barney, 1991; Wernerfelt, 1984). In the context of internal auditing, these resources encompass not only a skilled workforce and robust information technology infrastructure but also managerial capabilities and organizational culture. For the effective implementation of artificial intelligence in internal audit activities, enterprises need to leverage these resources efficiently.

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## LITERATURE REVIEW

In recent years, numerous studies have examined how AI can be applied in auditing to enhance audit quality. These studies have explored the role of AI in automating data-intensive audit tasks, enabling more detailed identification of high-risk transactions through pattern recognition and predictive analytics (Choi et al., 2022; Berghout & Fijneman, 2023; Fedyk et al., 2022; Puthukulam et al., 2021). At the same time, AI assists auditors in determining whether specific transactions require further examination and facilitates the rapid identification of trends and patterns within datasets (Struthers & Nesgood, 2020). Collectively, the research indicates that AI provides significant benefits for auditing activities, including cost reduction and efficient processing of large volumes of data, thereby improving overall audit effectiveness.

Merkhoufi (2024) evaluated the mutual impact of AI and information technology (IT) infrastructure on audit process quality in organizations in Algeria. The study indicated that a robust IT infrastructure plays a significant role in enhancing audit quality by providing auditors with the necessary tools and data resources. Furthermore, the research demonstrated that AI contributes substantial value to auditing activities through its ability to automate repetitive tasks and analyze large volumes of data with high accuracy.

Moreover, several studies have assessed the impact of AI on internal audit activities within enterprises. Singh (2021) analyzed the factors influencing the effectiveness of internal auditing and their effects on audit quality, focusing on auditor independence, objectivity, and competence. The study found a significant relationship between these factors and internal audit quality, while also highlighting the role of internal auditing in safeguarding stakeholder interests and ensuring compliance with corporate governance standards.

The study by Steira and Bangsund (2023) examined the impact of AI adoption in internal audit processes on the occurrence of internal control weaknesses in publicly listed companies in the United States. The findings indicate that integrating AI into internal audit activities contributes to enhancing the effectiveness of internal control systems over financial reporting by reducing the number of identified control deficiencies.

Although numerous studies have examined the role of AI in internal audit quality, empirical research on the impact of specific factors influencing AI adoption and its effect on internal audit processes and quality remains limited. The number of studies testing these relationships using advanced econometric models is still scarce. This gap hinders a comprehensive understanding of how organizational and auditor-related factors affect the practical effectiveness of AI in internal auditing and limits the ability to develop more accurate predictive models for audit quality when AI is applied.

## PROPOSED RESEARCH MODEL

*H1: Internal auditors' technological level positively affects the adoption of AI in internal auditing.*

Previous studies indicate that a high level of technological proficiency enables auditors to more easily access, understand, and utilize AI tools for data analysis, risk detection, and optimization of audit processes (Sun & Vasarhelyi, 2016; Kokina & Davenport, 2017). When auditors clearly perceive the benefits of AI, such as increased accuracy in data analysis, automation of control procedures, and enhanced work efficiency, they are more likely to support its implementation (Henry & Rafique, 2021). The rapid digitalization of audit activities imposes the need for auditors to adopt new technologies and methodologies, which can only be achieved through continuous training (Alli et al., 2022; Odeyemi, 2023). Bunget and Dumitrescu (2009) argue that auditors must enhance their IT capabilities to effectively conduct audits and identify risks arising from IT systems. Potential biases inherent in AI systems may pose risks to the reliability of audited financial information (Fedyk et al., 2022). Therefore, internal auditors need to be equipped with the knowledge and skills to address such situations. Additionally, technologically proficient auditors are often better able to apply data analytics software, automation tools, and algorithms to perform complex audit tasks, minimize errors, and increase the timeliness of reporting (Kokina & Davenport, 2017).

*H2: Administrator support positively affects the adoption of AI in internal auditing.*

According to the Resource-Based View (RBV), a lack of support from management may lead to reduced competitiveness and an inability to adopt new technologies (Garrison et al., 2015). Senior managers play a critical

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role in shaping strategic direction, allocating resources, and fostering an innovation-oriented culture to maximize the benefits of AI within organizations (Song et al., 2025). The implementation of AI requires a long-term strategy, including investments in financial and human resources. Without adequate resources, any investment in AI is unlikely to yield effective results (Khaled, 2022). When senior management demonstrates commitment, provides resources, and facilitates policies, personnel, and training, internal auditors are better able to access and utilize technological tools, thereby enhancing the effectiveness of AI adoption in audit processes.

*H3: Organizational culture positively affects the adoption of AI in internal auditing.*

Organizational culture, defined as a set of shared values used to address structural, human, and other factors influencing organizational effectiveness and success, plays a critical role in internal auditing (Kreitner & Kinicki, 1998). Recent studies indicate that organizational culture is a key determinant in promoting the adoption of AI in internal auditing. An innovative, change-supportive culture that encourages continuous learning is considered a positive factor, providing an environment that allows auditors to experiment, take risks, and develop the skills necessary for AI implementation (Wang, 2022). A culture that emphasizes responsibility, openness, and continuous learning can amplify the positive impacts of digital technology adoption on internal audit quality. Conversely, a culture that stifles creativity and open discussion may limit the benefits that digital technologies bring to internal audit activities (Dittenhofer, 2001).

*H4: Information technology infrastructure positively affects the adoption of AI in internal auditing.*

The development of IT infrastructure has significantly impacted internal audit activities within organizations (Chaveerug & Ussahawanitchakit, 2009; Mustapha & Lai, 2017). The application of IT in auditing processes enhances the ability to search for and exploit detailed information, analyze and process unusual transactions, conduct more comprehensive audits, improve audit processes continuously, and increase the timeliness of audit reporting. Alareeni and Hamdan (2022) studied the readiness of auditing firms in the Middle East to adopt AI and found that many firms were constrained by technical expertise and IT infrastructure limitations.

*H5: The adoption of AI in internal auditing positively affects the effectiveness of internal audit processes.*

Previous studies have extensively examined the impact of AI on audit quality. AI-based data analytics tools can enhance the efficiency and performance of auditing, thereby improving audit quality. AI can automate repetitive and time-consuming audit tasks, such as data entry, data validation, and documentation. This automation reduces the risk of human error and allows auditors to focus on more complex activities (Sihombing et al., 2023). AI also supports auditors in conducting more accurate risk assessments and predicting potential audit risks. AI-driven risk assessment tools can enhance audit quality by improving risk identification, resource allocation, and audit planning (Aljaaidi et al., 2023).

*H6: The adoption of AI in internal auditing positively influences audit quality.*

At the same time, audit process efficiency is selected as a mediating variable because it reflects the successful application of technology in the auditing process, which indirectly impacts audit quality. Ghafar (2024) emphasizes that technology optimizes processes, saves time, reduces costs, and enhances risk detection capabilities. According to Mpofu (2023), the use of AI in auditing induces significant changes in audit procedures as well as in the generation and quality of audit evidence.

*H7: Internal audit process efficiency positively affects audit quality.*

With the advancement of technology, the application of big data analytics, AI, and automation in auditing processes has been shown to enhance process efficiency, thereby improving audit quality. These technologies enable auditors to process large volumes of data quickly, accurately, and comprehensively, facilitating the detection of anomalies, errors, or fraud that traditional methods may struggle to identify (Nairi et al., 2021; Safonova & Alekseenko, 2022).

Based on theoretical foundations and previous empirical studies, the proposed research model aims to examine the impact of artificial intelligence on the auditing process and the quality of internal audit as follows:

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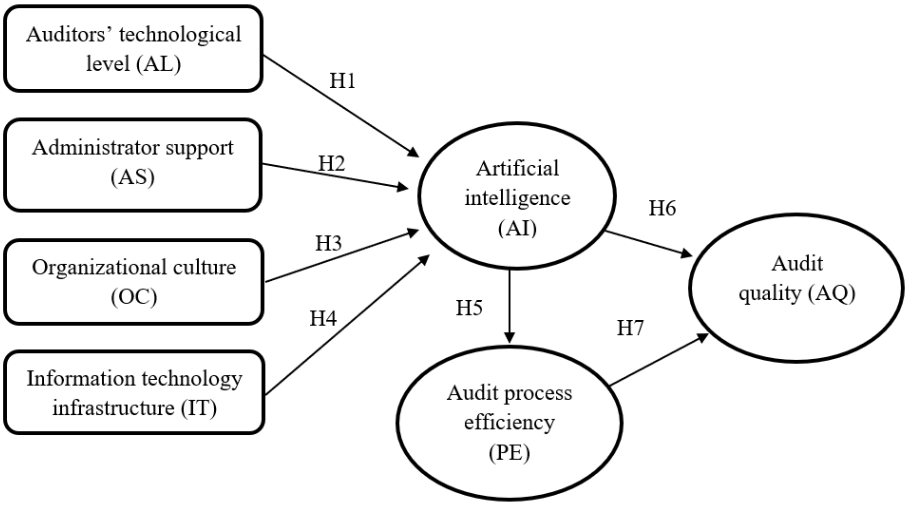


**Figure 1.** The Proposed Research Model

## METHODS

Data for this study were collected using a structured questionnaire, with all observed variables measured on a five-point Likert scale. The target respondents included members of the Board of Directors and internal auditors from companies listed on the Vietnamese stock market. The questionnaire was distributed electronically via email and Google Forms. Out of 334 questionnaires sent, 316 were returned, resulting in a high response rate of 94.6%. After data cleaning and removal of incomplete or invalid responses, 308 valid questionnaires remained, satisfying the required sample size for analysis. The collected data were subsequently analyzed using SPSS 26 and AMOS 24.

The study followed a systematic three-step procedure. First, the reliability of the measurement scales was evaluated using Cronbach's Alpha and item-total correlations to ensure their internal consistency and stability. Next, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted to assess convergent and discriminant validity, as well as the overall fit of the measurement model. Finally, structural equation modeling (SEM) was employed to examine the complex relationships among variables. Relationships with p-values below 0.05 were considered statistically significant, forming the basis for evaluating the proposed research hypotheses.

## RESULTS

The results of the Cronbach's Alpha test (Table 1) indicate that all measurement scales exhibit Cronbach's Alpha coefficients greater than 0.7, demonstrating good reliability. The item-total correlations for all observed variables within each scale exceed 0.6, and the Cronbach's Alpha if an item is deleted is lower than the overall Cronbach's Alpha for the scale, suggesting that no items need to be removed. Therefore, all scales included in this study are reliable, and all observed variables contribute positively to the reliability of the respective scales.

**Table 1.** Results of testing the reliability of the scale

| Factors | Code | Number of Items | Cronbach's Alpha | Corrected Item-Total Correlation |
|---|---|---|---|---|
| Auditor's technological level | AL | 5 | 0.864 | 0.649-0.708 |
| Administrator support | AS | 4 | 0.837 | 0.655-0.693 |
| Organizational culture | OC | 4 | 0.841 | 0.641-0.701 |
| Information technology infrastructure | IT | 4 | 0.832 | 0.613-0.716 |

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|---|---|---|---|---|
| Artificial intelligence | AI | 3 | 0.824 | 0.642-0.707 |
| Audit process efficiency | PE | 4 | 0.870 | 0.705-0.757 |
| Audit quality | AQ | 2 | 0.783 | 0.643-0.645 |

*(Source: Results analyzed using SPSS software)*

The Kaiser-Meyer-Olkin (KMO) test for the independent variables yielded a KMO value of 0.833, which falls within the acceptable range of 0.5 ≤ KMO ≤ 1, indicating that the data were suitable for exploratory factor analysis (EFA). Bartlett's test of sphericity was significant (Sig. = 0.000 < 0.05), confirming that the correlation matrix among the observed variables was not an identity matrix and that the variables exhibited linear relationships suitable for factor extraction.

**Table 2.** EFA analysis results

| | Factor | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| AL2 | .787 | | | | | | |
| AL3 | .778 | | | | | | |
| AL5 | .775 | | | | | | |
| AL1 | .709 | | | | | | |
| AL4 | .692 | | | | | | |
| AS3 | | .779 | | | | | |
| AS4 | | .772 | | | | | |
| AS2 | | .728 | | | | | |
| AS1 | | .718 | | | | | |
| OC3 | | | .783 | | | | |
| OC4 | | | .776 | | | | |
| OC2 | | | .773 | | | | |
| OC1 | | | .688 | | | | |
| IT1 | | | | .817 | | | |
| IT2 | | | | .766 | | | |
| IT3 | | | | .717 | | | |
| IT4 | | | | .684 | | | |
| AI1 | | | | | .827 | | |
| AI3 | | | | | .799 | | |
| AI2 | | | | | .720 | | |
| PE2 | | | | | | .836 | |
| PE4 | | | | | | .791 | |
| PE1 | | | | | | .771 | |

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| | | | | | | | |
|---|---|---|---|---|---|---|---|
| PE3 | | | | | | .768 | |
| AQ2 | | | | | | | .802 |
| AQ1 | | | | | | | .802 |

*(Source: Results analyzed using SPSS software)*

The EFA results for the four independent variables indicated an eigenvalue of 1.536 (> 1), suggesting that the extracted factor is statistically significant. The total variance explained was 65.994% (> 50%), and all factor loadings of the observed variables exceeded 0.5, confirming that each item contributed substantially to the extracted factor. These findings validate that the factor structure of the independent variables is both reasonable and reliable.

For the dependent variables AI, PE, and AQ, the KMO values were 0.714, 0.832, and 0.500, respectively, all exceeding the recommended threshold of 0.5, indicating that the data were suitable for factor analysis. The eigenvalues of the extracted factors were 2.221, 2.880, and 1.643 (> 1), suggesting that all factors were statistically significant. Bartlett's test of sphericity was significant (Sig. = 0.000 < 0.05), confirming the adequacy of the correlation matrices for EFA. The total variance explained by the factors was 74.030%, 72.010%, and 82.170% (> 50%), indicating that the extracted factors accounted for a substantial portion of the variance in the observed variables.

Thus, both the independent and dependent variables met all the necessary criteria regarding KMO values, eigenvalues, Bartlett's test, factor loadings, and the variance explained. These results confirm that the research data exhibit a clear factor structure, with all observed variables contributing significantly, and are suitable for subsequent analysis using structural equation modeling (SEM).

CFA was conducted to assess whether the observed variables accurately measured the underlying constructs of the research model. To evaluate model fit, several indices were examined: $\chi^2/df$ (CMIN/df) = 1.121, which is below the recommended threshold of 2, indicating a good fit; Comparative Fit Index (CFI) = 0.991, exceeding 0.95, indicating an excellent fit; Tucker-Lewis Index (TLI) = 0.989, above the 0.9 threshold, and Root Mean Square Error of Approximation (RMSEA) = 0.02, below 0.05, reflecting a good fit. These indices demonstrate that the overall model fit is satisfactory, and no significant correlations were observed among measurement errors, confirming that the observed variables adequately represent the intended factor structure.

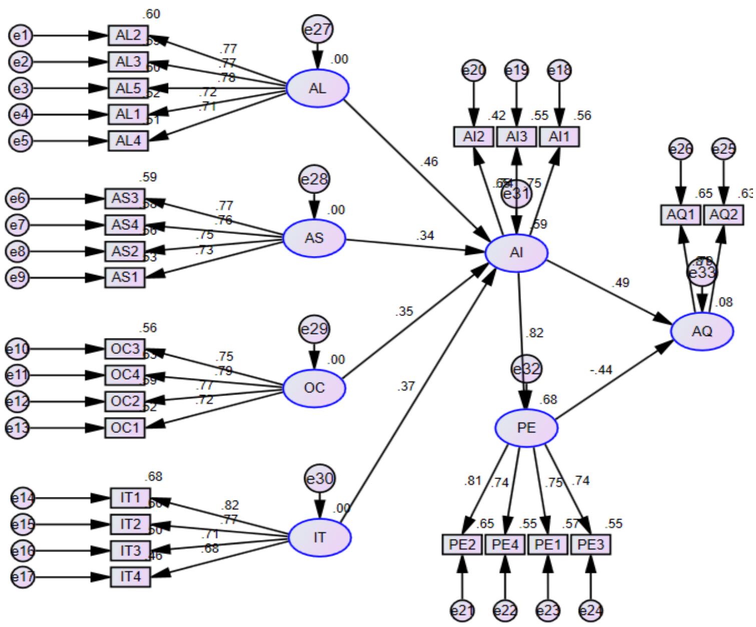


**Figure 2.** Results of the SEM Analysis

*(Source: Results analyzed using AMOS software)*

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The results of the analysis (Figure 2) indicate that the model fits the data well, with $\chi^2/df = 1.422$ (< 2), CFI = 0.966 (> 0.9), TLI = 0.963 (> 0.9), and RMSEA = 0.037 (< 0.05). All indices fall within the acceptable thresholds, confirming that the measurement model is consistent with the observed data. Table 3 presents the results of the correlations among the constructs in the research model.

**Table 3.** Correlations and Relationships Among Constructs in the Research Model

| Hypothesis | Correlations | | | Standardized Regression Weight | Standard Error (S.E.) | Critical Ratio (C.R.) | P-value | Conclusion |
|---|---|---|---|---|---|---|---|---|
| (H1) | AI | <--- | AL | 0.471 | 0.062 | 7.606 | 0.000 | Accepted |
| (H2) | AI | <--- | AS | 0.347 | 0.058 | 5.943 | 0.000 | Accepted |
| (H3) | AI | <--- | OC | 0.341 | 0.056 | 6.086 | 0.000 | Accepted |
| (H4) | AI | <--- | IT | 0.328 | 0.051 | 6.446 | 0.000 | Accepted |
| (H5) | PE | <--- | AI | 0.895 | 0.080 | 11.145 | 0.000 | Accepted |
| (H6) | AQ | <--- | AI | 0.564 | 0.217 | 2.605 | 0.009 | Accepted |
| (H7) | AQ | <--- | PE | 0.464 | 0.192 | 2.409 | 0,016 | Accepted |

*(Source: Results analyzed using AMOS software)*

The results of the SEM analysis indicate that all proposed research hypotheses were supported. Specifically, AL, AS, OC, and IT all have positive and statistically significant effects on AI, with standardized regression weights of 0.471, 0.347, 0.341, and 0.328, respectively, all with p-values of 0.000 (< 0.05). As a mediating factor, AI has a strong and significant impact on PE ($\beta = 0.895$; $p = 0.000$) and AQ ($\beta = 0.564$; $p = 0.009$). In addition, PE positively and significantly affects AQ ($\beta = 0.464$; $p = 0.016$). These findings indicate that the relationships within the research model are consistent, with independent variables influencing the mediating factor, which in turn affects the outcome variables, confirming both the suitability and reliability of the model's structure.

## DISCUSSION

First, the findings indicate that among the four independent variables, auditors' technological level has the strongest and most positive effect on the adoption of AI in internal auditing, with a standardized regression coefficient of $\beta$ = 0.471 (statistically significant). This demonstrates that auditors' technology level plays a crucial role in facilitating the integration of AI into the auditing process.

These results are consistent with previous studies by Bunget & Dumitrescu (2009), Sun & Vasarhelyi (2016), and Kokina & Davenport (2017), which suggest that auditors with strong technological knowledge and skills are better equipped to access, operate, and leverage AI tools effectively. High technological level not only enables auditors to understand the operational principles of AI systems but also supports them in assessing the appropriateness, reliability, and potential risks associated with the use of such technologies in the internal auditing process.

Second, administrator support has the second strongest positive effect on the adoption of AI in internal auditing, with a standardized regression coefficient of $\beta$ = 0.347 (statistically significant). This implies that commitment and support from administrators play a critical role in the implementation of new technologies, particularly AI-based solutions. These findings are consistent with the studies of Garrison et al. (2015) and Song et al. (2025). When administrators demonstrate clear support through strategic guidance, resource allocation, encouragement of innovation, and removal of psychological barriers, internal auditors are more likely to adopt AI applications in their auditing processes. Even organizations with advanced technological infrastructure may experience limited success in AI implementation without consistent support from senior management. Therefore, to enhance the adoption of AI in internal auditing, administrators at all levels should proactively foster innovation and ensure that internal auditors have access to the necessary resources.

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Third, organizational culture has the third strongest positive effect on the adoption of AI in internal auditing, with a standardized regression coefficient of $\beta = 0.341$ (statistically significant). This indicates that organizations fostering a culture of innovation, collaboration, and continuous learning provide a supportive environment that enables internal auditors to confidently apply and integrate AI into their auditing tasks. The findings highlight that, in addition to auditors' technological proficiency and managerial support, cultivating and maintaining an appropriate organizational culture is a crucial factor for enhancing the effectiveness of AI adoption in internal auditing. These results are in line with the studies of Wang (2022), Wiese et al. (2024), and Isensee et al. (2021).

Fourth, IT infrastructure has a positive effect on the adoption of AI in internal auditing, ranking fourth in strength among the surveyed factors, with a standardized regression coefficient of $\beta = 0.328$ (statistically significant). This indicates that improvements in IT infrastructure enhance the organization's capability to implement AI in internal auditing. However, while IT infrastructure provides the essential technical foundation for deploying AI in auditing tasks, its direct impact on AI adoption is less prominent compared to human-related factors, such as auditors' knowledge, skills, attitudes, and technological level, as well as administrators support. This finding is consistent with Hameed & Arachchilage (2017), who emphasized that human factors are often more decisive in AI implementation, whereas IT infrastructure primarily plays a supporting role.

Fifth, the adoption of AI in internal auditing has a substantial and positive impact on the efficiency of the internal audit process. The empirical evidence from this study suggests that by automating routine and repetitive auditing tasks, AI enables auditors to perform their work more quickly and accurately, thereby optimizing the overall efficiency of audit procedures. This improvement is not limited to speed but also extends to the consistency and quality of audit execution, allowing auditors to allocate more time to complex, judgment-based activities. These findings are in line with previous research by Joshi & Marthandan (2020) and Leocádio et al. (2024), which emphasized that the integration of AI into auditing processes can significantly enhance operational efficiency and reduce the time and effort required to complete standard audit tasks.

Sixth, the adoption of AI in internal auditing also exerts a positive influence on audit quality. AI's ability to process large volumes of data rapidly and with high precision helps mitigate risks associated with sample selection, reduces the likelihood of overlooking critical information, and enhances the overall reliability and completeness of audit reports. By providing auditors with timely and accurate insights derived from data analytics, AI supports more informed decision-making and improves the robustness of audit findings. These results corroborate the conclusions of Alotaibi (2023) and Leocádio et al. (2024), who highlighted that the application of AI in auditing strengthens evidence-gathering procedures and contributes to higher quality and more trustworthy audit outcomes. Taken together, these findings demonstrate that AI not only facilitates greater efficiency in audit processes but also enhances the credibility and reliability of audit results, underscoring its strategic value in modern internal auditing.

Seventh, the efficiency of the internal audit process has a positive effect on audit quality. An effectively managed audit process not only optimizes the collection, processing, and analysis of information in a comprehensive and accurate manner but also ensures that audit tasks are completed on schedule, minimizing risks and enhancing the detection of errors within the internal control system. When the internal audit process is well-structured and systematically organized, audit activities become more efficient and coherent, which in turn improves audit quality and increases the informational value provided to management, supporting timely and well-informed decision-making. These findings are consistent with the results of Qader & Cek (2024), emphasizing that the operational efficiency of the audit process is a key determinant of overall audit effectiveness.

## CONCLUSION

This study sheds light on the positive impact of AI on internal audit processes and audit quality in companies listed on the Vietnamese stock market. The analysis demonstrates that the adoption of AI not only enhances data processing efficiency and reduces errors within audit procedures but also enables auditors to identify risks at an early stage, thereby improving overall audit quality. AI has emerged as a powerful supporting tool that optimizes the audit process across all stages, from planning and risk assessment to audit execution and reporting of audit findings.

Moreover, the study highlights that the effectiveness of AI adoption in internal auditing largely depends on the technological competence of internal auditors and the support provided by senior management. Enhancing awareness of the role of information technology, as well as increasing investment in IT infrastructure, is essential to ensure that AI can maximize its potential in internal audit activities. Such efforts are crucial not only for managers and auditors but also for regulatory bodies in developing digital transformation strategies and improving the overall quality of internal auditing.

Although the study successfully achieved its research objectives, several limitations should be acknowledged. First, the research sample was limited to companies listed on the Vietnamese stock market, which may restrict the generalizability of the findings to non-listed companies or small- and medium-sized enterprises, where the adoption of AI in internal auditing may face greater challenges due to technological and resource constraints. Second, the study primarily relied on survey data collected from members of the Board of Directors and internal auditors, which may introduce potential bias due to subjective assessments. These limitations provide opportunities for future research to expand the sample scope and employ more advanced research models to analyze the impact of AI on internal audit quality across a broader range of organizations.

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