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The impact of artificial intelligence on internal audit quality amidst the challenges of Algeria's IT infrastructure

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***Abstract*---**This research aims to evaluate the mutual impact of artificial intelligence (AI) and information technology infrastructure on the quality of audit processes in Algerian organizations. The study adopted a structural modeling approach using SmartPLS to analyze data collected from a sample of internal auditors, academicians in the field of auditing, and professionals working in Algeria. The findings revealed several key results. First, a robust IT infrastructure significantly contributes to improving audit quality by providing auditors with the necessary tools and data. Second, the study confirmed that AI offers substantial value to audit processes by automating routine tasks and analyzing large volumes of data with high accuracy. Furthermore, the results indicated that the impact of AI and infrastructure is complementary, as each enhances the other. The infrastructure provides a suitable environment for AI application, while AI, in turn, leverages this infrastructure to achieve better results. In conclusion, investing in developing the infrastructure and adopting AI technologies represents a strategic investment for Algerian organizations. This investment contributes to improving audit quality, enhancing trust in financial reports, and achieving greater efficiency and effectiveness in operations.

***Keywords*---**Artificial intelligence, information technology infrastructure, audit quality, Algerian organizations.

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I. Introduction:

Artificial intelligence and information technology have emerged as indispensable tools for internal auditors to enhance the efficiency and effectiveness of their work. The digital transformation sweeping the modern world necessitates that internal auditors proactively adapt to these technological advancements and leverage them to improve performance and bolster efficiency.

AI has the potential to revolutionize audit and review processes, making them faster and more accurate, thereby reducing errors and enhancing overall audit quality. Moreover, information technology can provide robust tools for analyzing and developing internal control systems, aiding in the detection of any illicit activities or irregularities within financial operations. AI's capacity to analyze large datasets and identify anomalous or suspicious patterns empowers internal auditors to proactively uncover risks and potential misconduct.

Considering the challenges posed by Algeria's IT infrastructure, internal auditors face obstacles in adopting and implementing AI in their work. Nonetheless, the utilization of AI and information technology in internal auditing represents a significant pathway toward advancements and enhancements in auditor performance. Based on the foregoing, the following research question arises: To what extent does AI influence the job performance of internal auditors, and what role does Algeria's IT infrastructure play in supporting the impact of AI tools on the performance of internal auditors?

Sub-questions:

- Is there a statistically significant impact ($\alpha \leq 0.05$) of AI on audit quality in Algerian organizations?
- Is there a statistically significant impact ($\alpha \leq 0.05$) of IT infrastructure on audit quality in Algerian organizations?
- Is there a statistically significant impact ($\alpha \leq 0.05$) of AI on IT infrastructure?
- Is there a statistically significant impact ($\alpha \leq 0.05$) of AI, in conjunction with IT infrastructure, on audit quality in Algerian organizations?

Hypotheses:

- H0: There is no statistically significant impact ($\alpha \leq 0.05$) of AI on audit quality in Algerian organizations.
- H0: There is no statistically significant impact ($\alpha \leq 0.05$) of IT infrastructure on audit quality in Algerian organizations.
- H0: There is no statistically significant impact ($\alpha \leq 0.05$) of AI on IT infrastructure in Algerian organizations.
- H0: There is no statistically significant impact ($\alpha \leq 0.05$) of AI, when IT infrastructure is available, on audit quality in Algerian organizations.

The Importance and Objectives of the Study

The significance of this study stems from the increasing reliance on technology in auditing and oversight. This necessitates that internal auditors leverage AI to enhance their performance and professional development. However, Algeria's IT infrastructure faces numerous technological challenges that significantly hinder AI adoption and implementation. Thus, devising an effective and coordinated strategy to address these challenges is crucial for organizations to achieve their goals and improve operational efficiency. Moreover, there is an urgent need to enhance the technical and technological skills of internal auditors to keep pace with rapid advancements in information technology. By fully harnessing the potential of AI, internal auditors can conduct thorough and comprehensive data analyses, bolster their ability to detect anomalies and security and financial risks, and consequently achieve tangible improvements in their professional performance. Therefore, a comprehensive understanding of these modern technologies is essential for internal auditors, as it will empower them to seize new and innovative opportunities to achieve efficiency and effectiveness in their work.

II. Theoretical Literature

1. Artificial Intelligence and Internal Auditing:

Artificial intelligence is a field dedicated to creating machines capable of performing tasks that typically require human intelligence, such as data analysis and decision-making. AI relies on various techniques and methods, including machine learning, neural networks, and big data analytics. The Oxford Dictionary defines AI as "the ability of a computer or other machine to exhibit intelligent behavior, especially the ability to learn and make its own decisions." (Vrontis & All, 2023, p 2)

2. Artificial Intelligence and Internal Auditor Performance (Positives and Negatives):

AI can significantly enhance the efficiency of an internal auditor's work by analyzing data more quickly and accurately, thereby saving time and effort. Additionally, AI offers a wide range of other benefits, as it can support improved audit quality by detecting errors and deficiencies in work and providing recommendations to enhance operations and ensure compliance with local and international standards. Two key points can be highlighted regarding the impact of AI on auditor performance:

AI can significantly enhance the efficiency of an internal auditor's work. AI can analyze data quickly and efficiently, identify weaknesses in audit processes, and provide immediate solutions. Additionally, AI can provide recommendations to improve operations and enhance monitoring and evaluation processes. Recent technological advancements have led to significant leaps in AI development, with the creation of AI systems capable of processing vast amounts of data in a short time. Furthermore, these systems are equipped with machine learning algorithms that learn from data and improve their performance over time. Using AI, an

internal auditor can analyze organizational data in unprecedented ways. The system learns from the organization's historical data and uses this knowledge to improve audit performance and identify potential anomalies and problems in the system. (Baldwin & All, 2006, p 28).

Few studies in the applied literature have addressed the potential drawbacks of AI in audit and review processes. However, the potential use of AI to significantly reduce the need for human auditors may be one of the most significant challenges. Companies may no longer require human auditors to review their books as AI becomes more efficient at identifying errors and anomalies in data. This could lead to significant job losses in the audit sector and reduce the quality of financial audits (Hemin, 2017, p 6).

3. IT Infrastructure Challenges in Algeria

According to a study by Oxford University, cited by the Institute of Chartered Accountants in England and Wales (ICAEW 2016), 95% of accountants are at risk of job displacement due to the development of new automated technologies. Chassignol et al. (2018, p 19) mentioned that AI could threaten the security of financial data. As AI becomes better at identifying patterns in data, it may be able to identify sensitive information that should not be disclosed to external parties. If this information falls into the wrong hands, it could be used to exploit financial institutions or commit other crimes. Moreover, the literature also highlights the challenges of integrating vast amounts of structured and unstructured data to gain insights into a company's financial and non-financial performance (Kokina et al., 2017, p 2017).

Algeria's IT infrastructure suffers from a lack of updates and investment compared to many countries, both in the Arab world and internationally. This hinders the implementation of intelligent solutions and AI tools in both the public and private sectors, delaying the creation of a suitable environment for adopting AI technologies and modern technological advancements. A major obstacle faced by Algeria is its inability to manufacture IT and communications resources domestically. The country remains heavily reliant on foreign markets and almost entirely dependent on modern technological devices from developed countries such as those in the European Union or some Asian countries. Algeria's delay in technological adoption is due to several factors, including a lack of investment in existing IT and telecommunications infrastructure, a shortage of government guidance towards developing and strengthening digital infrastructure, and companies' inability to keep pace with modern and advanced technology due to a lack of training and qualification for human resources and the availability of necessary financial and technical resources. It is essential for the government to create a supportive and encouraging environment for the technology sector and provide opportunities for training and developing the technological and scientific skills of human resources. Establishing cooperation and strategic partnerships with the private sector, educational institutions, and research institutions is necessary to achieve effective and sustainable progress in the field of technology in Algeria. (Querini, 2019, p 67)

III. Applied Literature

The integration of Artificial Intelligence (AI) into the auditing profession has been a transformative force, particularly in regions like Algeria, where the challenges of information technology infrastructure present unique hurdles. The influence of AI on the job performance of internal auditors can be understood through various dimensions, including enhanced efficiency, improved audit quality, and the necessity for continuous professional development. This synthesis draws upon a wide array of scholarly articles to elucidate these themes. AI technologies have been shown to significantly enhance the efficiency of internal audit processes. For instance, Noordin et al. highlight that the use of AI in auditing allows for the automation of routine tasks, enabling auditors to focus on more complex analyses and strategic decision-making (Noordin et al., 2022).

This automation not only streamlines workflows but also reduces the time spent on data entry and processing, which is crucial in environments where internal auditors are often burdened with high volumes of data. Similarly, Bonsu et al. provide empirical evidence that AI contributes to better accounting practices by enhancing the reliability of financial information and reducing the potential for fraud (Bonsu et al., 2023). This is particularly relevant in Algeria, where the integrity of financial reporting is paramount for fostering trust among stakeholders. Moreover, the adoption of AI technologies is associated with improved audit quality. Seethamraju and Hecimovic emphasize that while AI tools can process vast amounts of data, the interpretation of this data still requires the professional judgment of auditors (Seethamraju & Hecimovic, 2022).

This interplay between AI capabilities and human expertise is critical, as auditors must evaluate management's assumptions and challenge conflicting information. The ability to leverage AI for data analysis while applying professional judgment enhances the overall quality of audits, which is essential in maintaining compliance with auditing standards. However, the integration of AI into auditing practices also presents challenges, particularly in terms of the existing information technology infrastructure. Al-Hattami notes that auditors must keep pace with rapid technological advancements to meet societal needs, which includes addressing the risks associated with computerized Accounting Information Systems (AIS) (Al-Hattami, 2021). In Algeria, where IT infrastructure may not be as robust as in more developed regions, the successful implementation of AI in auditing may require significant investment in technology and training. This is echoed by Kuncoro, who discusses the necessity for auditors to adapt to AI advancements to remain relevant in their roles (Kuncoro, 2023).

Training and continuous professional development are critical components in the successful adoption of AI in auditing. As highlighted by Ali et al., the digitization of auditing processes necessitates that internal auditors enhance their skills in data-driven methodologies (Alli et all, 2022). The challenges posed by the rapid digitization of audit activities compel auditors to adopt new technologies and methodologies, which can only be achieved through ongoing education and training. This need for skill enhancement is further supported by Odeyemi, who emphasizes the importance of balancing technological advancements with

maintaining audit quality and integrity (Odeyemi, 2023). The ethical considerations surrounding AI in auditing also warrant attention. Fedyk et al. discuss the potential biases inherent in AI systems, which can pose risks to the reliability of financial information (Fedyk et al., 2022). Auditors must be equipped to navigate these ethical dilemmas, ensuring that their reliance on AI does not compromise the quality of their work.

This is particularly pertinent in Algeria, where the regulatory framework may still be evolving in response to technological advancements. Furthermore, the role of AI in enhancing risk management capabilities cannot be overlooked. Ríkharðsson et al. indicate that AI tools can significantly improve auditors' ability to detect anomalies and assess risks, thereby enhancing their overall effectiveness (Ríkharðsson et al., 2022). In a landscape where financial fraud and misreporting are prevalent, the ability to leverage AI for risk assessment is invaluable. This capability is particularly crucial for internal auditors in Algeria, who must navigate a complex regulatory environment while ensuring compliance and accountability.

The literature also suggests that the adoption of AI in auditing is still in its nascent stages, with many firms yet to fully embrace these technologies. Kend and Nguyen note that the integration of AI and other emerging technologies in the auditing profession is still evolving, indicating that the full potential of AI has yet to be realized (Kend & Nguyen, 2020). This presents both a challenge and an opportunity for internal auditors in Algeria, as they must not only adapt to these changes but also advocate for the necessary investments in technology and training. In conclusion, the influence of AI on the job performance of internal auditors in Algeria is multifaceted, encompassing improvements in efficiency, audit quality, and risk management, alongside significant challenges related to technology infrastructure and ethical considerations. The successful integration of AI into auditing practices will require a concerted effort towards training and development, as well as a commitment to maintaining the integrity of the audit process. As the landscape of auditing continues to evolve, internal auditors in Algeria must remain vigilant and proactive in adapting to these changes to enhance their performance and the overall quality of audits.

IV. Practical aspect :

1. Population and Sample of the Study:

The population of this study consisted of internal auditors and academics in the field of auditing who are active in Algeria. A simple random sample was selected from this population, based on the Stephen Thompson formula to determine the optimal sample size. Given the geographical characteristics of the population, electronic questionnaires were randomly distributed. After collecting 120 responses, the data collection process was stopped. After data cleaning and removing invalid responses, the final sample size was 100, which is consistent with the study's requirements

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2. The Hypothetical Model of the Study:

Based on the existing theoretical framework regarding the relationship between artificial intelligence and audit quality considering Algeria's information and communication technology infrastructure, a hypothetical model was formulated to test this relationship in the Algerian context. This model seeks to answer research questions related to the extent to which AI affects the quality of the internal audit process and the effectiveness of the information and communication technology infrastructure in mediating the relationship between the variables. This was achieved by collecting the opinions of a sample of experts in internal auditing, including academics and practitioners; the following figure illustrates the hypothetical model of the study:

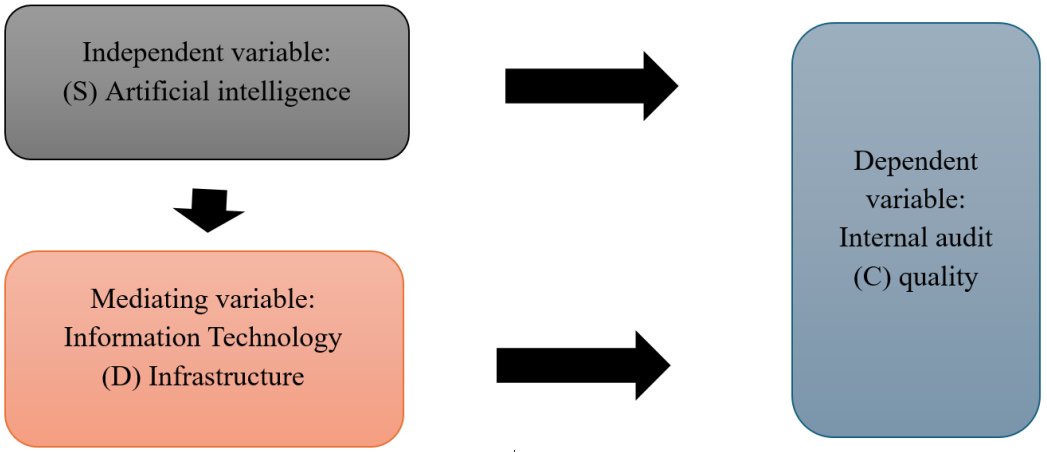

Figure 01: the hypothetical model of the study
Source: Prepared by the researchers Based on previous studies

3. Study Instrument:

The current study relied on a questionnaire as the primary data collection tool. The questionnaire consisted of two parts: the first to collect demographic information about the sample members, and the second to measure the research variables. The second part of the questionnaire was designed around three main axes, where a set of statements was formulated to measure each axis. A five-point Likert scale was used to measure the extent to which the sample members agreed or disagreed with these statements, with the highest score (5) given for complete agreement and the lowest score (1) for complete disagreement. The content of the questionnaire is summarized in the following table:

Table 1: Summary of the Questionnaire Content

Part	Axes	Statements
Part I	Age, Educational Qualification, Specialization, Professional Experience, Profession	
Part II	Artificial Intelligence (AI)	S1-S5
	Information Technology Infrastructure (IT)	D1-D7
	Internal Audit Quality (IAQ)	C1-C7

Source: Prepared by the Researchers

4. Statistical Methods

The quantitative data collected was analyzed using structural equation modeling with the partial least squares (PLS-SEM) approach, employing the SmartPLS 4 software. The analysis comprised two main phases: the first involved evaluating the measurement model, aimed at assessing the suitability, validity, and reliability of the measured indicators for the latent variables. The second phase focused on evaluating the structural model, aimed at testing the hypothesized causal relationships between the latent variables. The analysis results were used to evaluate the research hypotheses and interpret the relationships between the variables, contributing to the achievement of the study's objectives.

5. Measurement Model Analysis (Outer Model):

The analysis of the measurement model is divided into two main parts: Convergent validity refers to the degree to which the items that constitute a scale consistently measure the intended theoretical construct. According to (Hair Jr, Hult Ringle, and sarstedt (2016), convergent validity can be evaluated through three primary criteria:

Table 2: Convergent Validity Indicators

Criterion	Value
Factor Loadings	Greater than 0.5
Composite Reliability	Greater than 0.7
Average Variance Extracted (AVE)	Greater than 0.5

Source: Prepared by the researchers based on Hair Jr, Hult, Ringle, and Sarstedt (2016)

4.1 Discriminant validity

The model's validity is assessed by measuring the factor loadings of each factor in the adopted model, as shown below:

Table 3: Factor Loadings for the Measurement Model

factor	Outer loadings	factor	Outer loadings
c1 <- c	0.731	d4 <- d	0.670
c2 <- c	0.405	d5 <- d	0.226
c3 <- c	0.792	d6 <- d	0.362
c4 <- c	0.647	d7 <- d	0.632
c5 <- c	0.914	s1 <- s	0.774
c6 <- c	0.386	s2 <- s	0.362
c7 <- c	0.234	s3 <- s	0.844
d1 <- d	0.708	s4 <- s	0.793
d2 <- d	0.740	s5 <- s	0.852

Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Referring to the previous table, it appears that most of the factor loadings for each factor in the study are greater than 0.5, indicating that these factors represent their respective constructs well and are statistically acceptable according to (Hair Jr. et al., 2016). However, some items exhibited factor loadings significantly below 0.5. Specifically, these items were (S2) in the first factor (Artificial Intelligence), (D5 and D6) in the second factor (IT Infrastructure), and (C2, C6, and C7) in the third factor (Internal Audit Quality). Consequently, all items with loadings below 0.5 were removed, and the factor loadings were reassessed, as shown in the following table:

Table 4: Factor Loadings of the Modified Model (Final Model)

factor	Outer loadings	factor	Outer loadings
c1 <- c	0.841	d4 <- d	0.637
c3 <- c	0.844	d7 <- d	0.708
c4 <- c	0.544	s1 <- s	0.694
c5 <- c	0.608	s3 <- s	0.579
d1 <- d	0.499	s4 <- s	0.906
d2 <- d	0.755	s5 <- s	0.857

.Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Referring to the results presented in the table above, it can be concluded that the internal consistency of the items for each factor in the questionnaire is satisfactory, as the factor loadings (FL) are greater than 0.5 for all items in each factor. However, there is a single exception related to the loading of item (D1) in the IT Infrastructure factor (D), which was very close to the threshold value of 0.5, with a loading of 0.499, almost equal to the threshold value.

4.2 Reliability of the Measure (Convergent Validity)

The following table presents the numerical values obtained for the three convergent validity criteria, which serve as evidence of the consistency of the items constituting the measures in measuring the intended theoretical construct:

Table 5: Reliability and Validity Assessments

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Artificial Intelligence (S)	0.696	0.808	0.521
Information Technology Infrastructure (D)	0.650	0.749	0.512
Internal Audit Quality (C)	0.759	0.850	0.593

.Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Cronbach's alpha, a measure of internal consistency, indicates that the items within each scale of the questionnaire are highly correlated. As the Cronbach's alpha values for all scales exceeded the acceptable threshold of 0.70, this suggests that the questionnaire has a high level of reliability, meaning that it can be relied upon to produce consistent results when repeated under similar conditions.

Additionally, the **composite reliability (CR)** coefficient was used to assess the extent to which the items constituting the scales are consistent. The CR coefficient represents the proportion of shared variance among the items relative to the total variance and is a strong indicator of reliability. According to (Hair Jr. et al., 2016), the recommended value for CR is 0.7 or higher. The results in the table indicate that the CR values for all scales exceed this threshold, indicating a high level of reliability.

Furthermore, the **average variance extracted (AVE)** was used to assess the extent to which the latent construct represents the indicators associated with it. AVE represents the percentage of variance in the indicators that is explained by the latent construct. According to the established recommendations, the AVE value should exceed 0.5 to ensure that the factor explains a substantial proportion of the variance in its indicators. The results show that all factors achieved AVE values above 0.5, indicating that the latent constructs adequately explain the variance in the data.

5. Discriminant validity:

The **Fornell-Larcker criterion** indicates the extent to which variables are distinct from each other, that is, the degree to which there is no overlap between them. In other words, each variable should represent a specific theoretical construct and not share variance with other variables. The results in the table indicate that the Fornell-Larcker criterion values for all variables meet the required criteria, confirming the absence of overlap between the variables and thus fulfilling the discriminant validity criterion.

Table 6: Discriminant Validity Results for the Basic Study Model

Independent Variable \ Dependent Variable	Artificial Intelligence (S)	Information Technology Infrastructure (D)	Internal Audit Quality (C)
Artificial Intelligence (S)	0.72206		
Information Technology Infrastructure (D)	0.309883	0.657267	
Internal Audit Quality (C)	0.237528	0.322835	0.76995

.Source: Developed by the researchers based on the outputs of (SMART PLS 4)

The results of the measurement model analysis, through the assessment of convergent and discriminant validity, confirmed the validity and reliability of the items used to measure the research variables. Based on these reassuring results, we can proceed to the structural model analysis to evaluate the relationships between latent variables with high confidence in the validity of the data used. The following is the hypothesized model of our study after the necessary modifications:

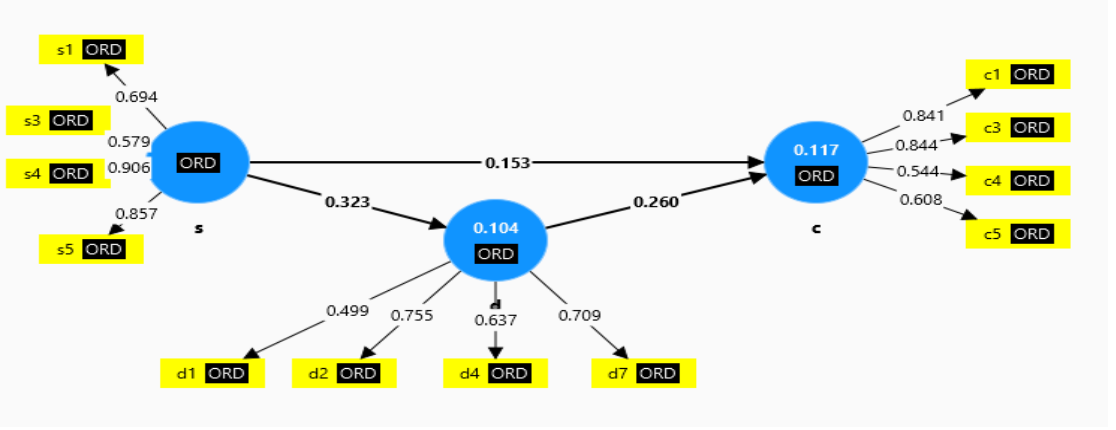

Figure 2: The Modified Research Model

6. Structural Model Analysis (Inner Model):

After confirming the validity and reliability of the measurement model through the assessment of convergent and discriminant validity, the study moves to the stage of evaluating the structural model. This analysis aims to assess the model's ability to explain the causal relationships between latent variables. A set of well-established statistical criteria in the research literature was selected to evaluate the fit of the proposed structural model, the most important of which are:

- Multicollinearity test among the study's factors (variables).
- Coefficient of determination (R^2)
- Effect size (f^2)
- Hypothesis testing (t-statistic)
- Multicollinearity test

6.1 Multicollinearity test

among the factors of each model: To test the multicollinearity problem, the Variance Inflation Factor (VIF) was adopted. The presence of multicollinearity or a strong correlation between any two factors is judged if the VIF value is greater than 10.

Table 7: Variance Inflation Factor for the Study Model

factor	VIF	factor	VIF
c1	2.52	d4	1.20
c3	1.58	d7	3.18
c4	4.27	s1	3.18
c5	4.61	s3	3.04
d1	3.54	s4	2.03
d2	2.10	s5	1.48

Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Based on the results presented above, it appears that the Variance Inflation Factor (VIF) values for each item in the questionnaire within the basic model are significantly less than 10. Therefore, there is no multicollinearity among any of the model's factors.

6.2 Coefficient of Determination (R^2):

The coefficient of determination represents the overall explanatory power of the model.

Table 8: Explanatory Power of the Study Model

	R-square	R-square adjusted
D	0.352	0.345
C	0.443	0.431

Source: Developed by the researchers based on the outputs of (SMART PLS 4)

The coefficient of determination for the basic model was found to be (R^2=0.443), which falls within the range of ($0.25 < R^2 < 1$). According to Cohen (1988), this explanatory power can be considered high, meaning that the explanatory and mediating variables in this model contribute to explaining 44.3% of the variations in audit approaches. The remaining 55.6% is attributed to other factors not included in the model but accounted for by the margin of error.

6.3 Effect Size (f^2):

Regarding the effect size (f^2), it explains the ability of each independent variable to explain the dependent variable individually. It is worth noting that the (J-F 2017) criterion was used to determine the degree of influence of both the independent

and mediating variables on the dependent variable. The results are presented in the table below:

Table 9: Effect Size (f^2) Results for the Study Model

f-square	Paths
0.384	IT infrastructure (D) to the quality of external audit (C)
0.124	artificial intelligence (S) to the quality of internal audit (C)
0.169	artificial intelligence (S) to IT infrastructure (D)

Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Based on the results presented in the table above, the effect of the "Artificial Intelligence Usage (S)" variable on external audit quality can be classified as relatively low or weak, as the effect size was 0.124, falling within the range of 0.02-0.15.

For the effect of the "Artificial Intelligence Usage (S)" variable on the "Digital Auditing (D)" variable, the effect size was 0.38, which can be classified as high, considering that this value was greater than 0.35.
The effect of the "Digital Auditing (D)" variable on external audit quality (C) can be classified as moderate, as the effect size was 0.16, falling within the range of 0.16-0.35.

7. Measurement Model Results for the Paths:

In this stage, we will attempt to estimate a measurement model that examines the effects of both the mediating and independent variables on the dependent variable, as well as the effect of the independent variable on the mediator. The ordinary least squares method will be used for estimation, and the results are presented in the following table:

Table 10: Table summarizing the estimated parameters for the paths

P values	T statistics (|O/STDEV|)	Standard deviation (STDEV)	Sample mean (M)	Original sample (O)	Tracks
0.002	2.304	0.125	0.583	0.288	**artificial intelligence (S) to IT infrastructure (D)**
0.000	3.303	0.119	0.627	0.393	**IT infrastructure (D) to the quality of external audit (C)**
0.472	0.72	0.146	0.141	0.105	**artificial intelligence (S) to the quality of internal audit (C)**

Source: Developed by the researchers based on the outputs of (SMART PLS 4)

Regarding the path from the artificial intelligence variable (S) to the information technology infrastructure (D), the effect (path coefficient) reached a value of (0.28) with a t-statistic of (). This value is significantly larger than the corresponding critical value at a 5% significance level. Therefore, the alternative hypothesis of the Student's t-test can be accepted, indicating that the hypothesized effect from the AI variable to the intermediary variable, information technology infrastructure, is statistically significant.

On the other hand, the path coefficient from information technology infrastructure (D) to internal audit quality (C) was (). The associated t-statistic of () is significantly larger than the critical value at a 5% significance level, considering that the p-value for this path is (0.00), which is less than the critical value of (0.05). Consequently, the alternative hypothesis for this test was also accepted.

The t-statistic for the path from artificial intelligence (S) to internal audit quality (C) was (). This value is not statistically significant at the 5% level, given that the associated p-value of (0.47) is much larger than the critical value of (0.05). In other words, the calculated t-statistic is significantly smaller than the corresponding critical value at the 5% significance level. Thus, the alternative hypothesis of the Student's t-test, which posits the existence of an effect from the independent variable to the dependent variable at the 5% significance level, can be rejected.

7 Hypothesis discussion

Hypothesis 1: The Impact of Artificial Intelligence on Audit Quality

"The first hypothesis stated that: 'There is no statistically significant effect at the significance level of (0.05) of artificial intelligence on audit quality in Algerian institutions.' Regarding the first hypothesis, which states that there is no significant statistical effect at a significance level of less than (0.05) of the artificial intelligence dimension on audit quality in Algerian institutions, the Fisher statistic indicates a weak effect. The Fisher statistic for the model, as shown in Table (09), was (0.12), which is greater than the minimum reference value of (0.02) according to Cohen (1988). Based on the calculated value of the Student's t-test, which was significantly less than the corresponding tabular value at the 5% significance level (1.96), we can reject the first null hypothesis, which states that there is no statistically significant effect at the significance level of (0.05) of artificial intelligence on audit quality in Algerian institutions. This finding aligns with the theoretical framework, as artificial intelligence tools such as machine learning and big data analysis help auditors detect errors and fraud more quickly and accurately. They also contribute to improving the efficiency of audit processes and reducing the time and effort involved. Despite the benefits offered by artificial intelligence, other factors influence audit quality, such as auditor competence, the work environment, and the quality of available data. These factors may mitigate the impact of artificial intelligence. The Fisher statistic suggests that the relationship is not very strong. This means that there are other factors besides artificial intelligence that play a larger role in explaining the differences in audit

quality among institutions. Several reasons can explain the weakness of this relationship, including:

- Lack of data: The lack of high-quality data on the use of artificial intelligence in auditing in Algeria is one reason for the weak relationship.
- Limited technology adoption: Algerian institutions are slow to adopt artificial intelligence technologies, limiting their impact on audit quality.
- Human factors: Auditor competence and experience play a crucial role in audit quality, regardless of the use of artificial intelligence tools.

Hypothesis 2: The Impact of IT Infrastructure on Audit Quality

"The second hypothesis stated that: 'There is no statistically significant effect at the significance level of (0.05) of IT infrastructure on audit quality in Algerian institutions.' Regarding the second hypothesis, the results of the structural equation modeling showed a significant statistical effect of the use of IT infrastructure on audit quality, and the value of this effect was estimated at (0.59). The positive sign of this parameter indicates the positive impact of the availability of IT infrastructure on the quality of internal auditing in Algerian economic institutions. This effect is classified as moderate, as the Fisher statistic for the model, shown in table (+), was (0.21), which falls within the range for a moderate effect level (0.16-0.35) according to Cohen (1988). Based on the calculated value of the Student's t-test, which was significantly greater than the corresponding tabular value at the 5% significance level (1.96), we can reject the second null hypothesis, meaning that there is a significant statistical effect at the significance level of (0.05) of IT infrastructure on audit quality in Algerian institutions. This implies that improving IT infrastructure leads to improved audit quality. In other words, when the infrastructure is good and advanced, auditors are able to use more advanced tools and techniques, helping them detect errors and fraud more quickly and accurately.

Hypothesis 3: The Impact of AI on IT Infrastructure

"The third hypothesis stated that: 'There is no statistically significant effect at the significance level of (0.05) of artificial intelligence on IT infrastructure in Algerian institutions.' Regarding the fourth hypothesis, the results of the structural equation modeling showed a significant statistical effect of artificial intelligence on IT infrastructure. The value of this effect was estimated at (0.28), which is considered statistically significant given that the associated Student's t-statistic is significantly larger than the tabular value (1.96) at the 5% significance level. Furthermore, Fisher's statistic for this path was (), indicating a moderate effect based on this statistic. Therefore, we can reject the third null hypothesis, which states that 'there is no statistically significant effect at the significance level of (0.05) of artificial intelligence on IT infrastructure in Algerian institutions.' This means that the adoption of artificial intelligence by institutions drives them to develop their IT infrastructure. In other words, when an institution wants to benefit from artificial intelligence, it needs to provide the necessary hardware, software, and networks to operate these technologies."

Hypothesis 4: The Combined Impact of AI and IT Infrastructure on Audit Quality

"The fourth hypothesis stated that: 'There is no statistically significant effect at the significance level of (0.05) of artificial intelligence, in the presence of IT infrastructure, on audit quality in Algerian institutions.' The combined effect of the artificial intelligence variable on audit quality, in the presence of IT infrastructure, was $(0.39 + 0.28 = 0.67)$. Given that the probability value for the combined paths is statistically significant, and the positive sign of this value indicates a positive impact of the artificial intelligence variable on internal audit quality within the context of IT infrastructure, from the perspective of internal auditors and academics working in Algerian economic institutions. Therefore, we can reject the fourth null hypothesis. The cumulative impact: Artificial intelligence and IT infrastructure work together to enhance audit quality. In other words, the existence of a good infrastructure provides the necessary foundation for the application of artificial intelligence, and artificial intelligence, in turn, benefits from this infrastructure to achieve better results. The results also indicate that artificial intelligence adds additional value to audit quality even when the infrastructure is good. In other words, artificial intelligence is not merely a tool that uses infrastructure, but it is an active factor in improving efficiency and effectiveness.

V. Conclusion

This study has revealed a pivotal role for artificial intelligence and IT infrastructure in enhancing audit quality within Algerian institutions. However, it is essential to acknowledge the challenges associated with adopting these technologies, such as a shortage of expertise and skills, high costs, and data security concerns. Therefore, realizing the full potential of artificial intelligence necessitates a concerted effort from both government and private sector institutions. A series of significant findings has been reached, confirming the impact of both artificial intelligence and IT infrastructure on audit quality in Algerian organizations. The statistical analysis revealed a positive and statistically significant relationship between these three variables. Firstly, the study established that IT infrastructure plays a crucial role in improving audit quality. A robust infrastructure provides auditors with the necessary tools and techniques to perform their duties efficiently and accurately. Secondly, the results demonstrated that artificial intelligence offers added value to audit quality, whether through enhancing the efficiency of audit processes or through more accurate detection of errors and fraud. Thirdly, the study unveiled an interactive effect between artificial intelligence and infrastructure, with each reinforcing the other's impact on improving audit quality. Based on these findings, a set of recommendations can be drawn for Algerian institutions and policymakers:

- **Investment in infrastructure:** Algerian institutions should invest in developing their IT infrastructure to provide a suitable working environment for implementing AI technologies.
- **AI adoption:** Institutions should adopt AI technologies and train their staff to use them.
- **Clear strategies:** Institutions should develop clear strategies for integrating AI into audit processes.

- **Collaboration with experts:** Institutions should collaborate with AI experts to develop customized solutions.
- **Developing regulatory frameworks:** Policymakers should develop regulatory frameworks that encourage the adoption of AI in the auditing field. **References**

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