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The Risks of Artificial Intelligence Technologies and Their Impact on The Performance of Accounting Information Systems in Iraqi Banks :An Applied Study

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Abstract

This study aims to analyze the impact of AI risks on the performance of accounting information systems in Iraqi banks, given the rapid digital transformation of the financial sector. The study was based on a key question: the nature of the relationship between technical risks arising from the use of AI, such as limited transparency and oversight, software bugs, and security threats and the efficiency of accounting information systems in terms of accuracy, reliability, and speed. A descriptive-analytical approach was adopted, and data were collected via a 50-question questionnaire distributed across multiple axes. The questionnaire targeted a purposive sample of 100 employees distributed across five Iraqi banks. The data was analyzed using SPSS, and the study found a strong, statistically significant positive correlation between employees' perceptions of AI risks and improved accounting system performance. It also revealed statistically significant differences in risk perceptions based on gender, educational qualifications, and administrative department. The study also revealed that weak transparency and oversight represent a significant obstacle to integrated performance, even with the presence of advanced AI tools. The study recommended adopting a smart governance framework that keeps pace with technological advancements, while enhancing training and awareness among all employees about the risks of artificial intelligence, to ensure the safe and effective use of accounting information systems in the banking environment.

Keywords: *Artificial intelligence, accounting information systems, IT governance*

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Introduction

In light of the rapid technological developments witnessed worldwide, artificial intelligence (AI) has emerged as one of the most influential innovations in the structure of administrative and financial systems, particularly in banking institutions, which rely heavily on the accuracy and reliability of accounting information systems. AI has become a strategic tool for banks, enabling greater operational efficiency and higher levels of automation, data analysis, and decision-making. However, despite their advantages, these technologies are not without potential challenges and risks that may negatively impact the performance of accounting systems and threaten the reliability, accuracy, and confidentiality of accounting information. From this perspective, this study gains importance by shedding light on the nature of the risks associated with AI technologies and their impact on the efficiency and effectiveness of accounting information systems in Iraqi banks, particularly in light of the complex regulatory and economic environment facing Iraqi financial institutions as a result of digital transformations, economic pressures, and security challenges. The study also seeks to analyze the relationship between the use of artificial intelligence and the risks accounting systems may face, such as data breaches, algorithmic biases, overreliance on automation, and reduced human interaction. This is achieved through an applied methodology based on a field study of a sample of banks operating in Iraq. The importance of this research lies in its ability to provide practical recommendations to Iraqi banking institutions on how to manage these risks and employ artificial intelligence technologies safely and effectively. This will enhance transparency in the accounting system, improve the quality of financial reports, and increase the efficiency of administrative and financial decision-making.

Artificial intelligence (AI) technologies represent a significant technological development in banking and accounting information systems, offering significant potential to improve the accuracy and speed of financial data processing and analysis. However, this progress is accompanied by the emergence of numerous risks that could negatively impact the quality and performance of these systems. These risks include information security risks, software or algorithmic errors, lack of transparency, and overreliance on automation. In the Iraqi context, these risks are exacerbated by the structural challenges facing the banking sector, including weak digital infrastructure, a lack of specialized skills, and weak regulatory frameworks regulating the use of AI. The absence of field studies that accurately assess the impact of these risks on accounting information systems in Iraqi banks further complicates the process of making effective decisions to address them. Therefore, the study highlights the need to understand the nature of these risks and the extent of their impact on the performance of accounting systems within Iraqi banks to ensure the safe and effective use of AI technologies.

Main research problem question:

What are the risks of artificial intelligence technologies, and how do these risks affect the performance of accounting information systems in Iraqi banks?

The importance of this study stems from the nature of the topic it addresses, which is :

1- The growing overlap between artificial intelligence and accounting information systems, especially in the Iraqi banking sector, which faces significant challenges in light of the global digital transformation and the rise in cyber and financial risks.

2 - Artificial intelligence technologies are now being employed in various functions, from processing accounting transactions and financial analysis to predicting risks and detecting manipulation and fraud.

3- Despite the advantages these technologies offer in terms of efficiency, speed, and accuracy, they may also generate technical and strategic risks that threaten the credibility and accuracy of accounting information, such as database hacking or excessive reliance on non-transparent algorithms.

4 - The importance of the study also emerges in the Iraqi context specifically, where the digital banking environment is still in its development phase, making institutions more vulnerable to these risks, given the weakness of the technical and legislative infrastructure, and the urgent need for a thorough understanding of the risks associated with artificial intelligence applications.

5 - This study also aims to fill a knowledge gap in the Arab and Iraqi literature on this topic by providing a comprehensive academic and applied analysis of the relationship between artificial intelligence and the performance of the accounting system.

This study aims to achieve a set of scientific and practical objectives that seek to deepen understanding of the challenges that **...**Artificial intelligence technologies are being applied in the accounting systems environment within Iraqi banks.

1- Analyzing and evaluating the impact of the risks of artificial intelligence technologies on the performance of accounting information systems in terms of efficiency, accuracy, and security .

2- Identify the main types of risks associated with the use of artificial intelligence technologies in the accounting environment, whether security, technical, legislative, or regulatory risks.

3- Studying the extent to which banking administrations in Iraq are aware of these risks, and the ways to deal with them in practical reality.

4- Analyzing the relationship between the level of use of artificial intelligence in accounting operations and the quality of financial reports issued by banks.

5- Evaluating the extent of the impact of these risks on the efficiency of the accounting system in achieving its objectives of control ,analysis, accuracy, and speed.

6- Proposing a set of recommendations and procedures that would mitigate the effects of these risks and ensure the safe and effective use of artificial intelligence technologies in accounting information systems.

7- Providing a conceptual framework that helps researchers and practitioners understand the interaction between technological innovation and accounting risks in the Iraqi banking context.

The first main hypothesis (H1):

There is a statistically significant relationship between the risks posed by artificial intelligence technologies and the accuracy of accounting information systems in Iraqi banks.

- Interpretation: Whenever increased sharpness Risks Associated By applying Artificial Intelligence (such as Algorithms, not minute or mistakes in data), decreased accuracy Quality Reports accounting

The second main hypothesis (H2):

risks negatively impact the efficiency of accounting information systems in Iraqi banks.

- Interpretation: It is possible that Lead Risks like Malfunctioning Technology, a deficiency in the Transparency algorithm, or an ill-designed order, can affect the operational efficiency of the system for the system Accountant.

The third main hypothesis (H3):

The heightened cybersecurity risks associated with artificial intelligence technologies are reducing the reliability of accounting information systems in Iraqi banks.

- Interpretation: Threats like breakthrough Data or leaked information affect the bezel's reliability and privacy Information accounting produced.

Study Contribution :This study contributes to a qualitative addition to the Arab academic literature, particularly the Iraqi one, by addressing a recent and increasingly important topic: the relationship between artificial intelligence risks and the performance of accounting information systems in the banking environment. This study is one of the few—if not rare—attempts to systematically link technical developments in artificial intelligence to the accounting and control aspects of Iraqi banks, thereby enhancing the research's innovative dimension. From a theoretical perspective, the study contributes to building an integrated scientific framework for classifying and interpreting the types of risks arising from the use of artificial intelligence in accounting systems, and clarifying the mechanisms of their impact on the accuracy, efficiency, and security of accounting information. From a practical perspective, the study provides a practical tool for Iraqi banks to diagnose the technological risks associated with artificial intelligence, helping them develop effective strategies to manage them and mitigate their potential impacts. The research results may also contribute to improving internal control procedures in accounting systems and enhancing the role of technological governance within banks, in line with international standards for information security and financial reporting quality. Therefore, this study is not limited to academic analysis but also serves as a practical reference for policymakers, auditors, and system developers to achieve a balance between the benefits of artificial intelligence and its risks to the financial and accounting system in a complex banking environment such as Iraq.

Table 1: Previous studies

number	Study title	Authors / Year	Study objectives	Main results	Similarities with the current study	Differences
1	The Impact of Artificial Intelligence on Financial Reporting	Li et al. (2021)	Analyzing the impact of artificial intelligence technologies on the quality of financial reports	Artificial intelligence contributes to increasing efficiency and improving prediction.	It intersects with our research into the impact of artificial intelligence on accounting performance.	Focused on the general financial side, not on the banking sector or risks.
2	Risks of AI Implementation in	Zhang & Gao (2020)	A study of the technical and regulatory	There are security and algorithmic risks that	They are consistent in their focus on	It did not address the practical reality in a

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	Accounting Systems		risks resulting from the use of artificial intelligence in accounting	threaten the accuracy and reliability of the systems.	risks and impact on the accounting system.	specific banking environment.
3	Artificial Intelligence in the Gulf Banking Sector	Al-Hadhrami & Al-Matari (2022)	Measuring the readiness of Gulf banks to use artificial intelligence	The risks are high due to the weak legal structure.	Close to the Iraqi environment in terms of structural challenges	Focused on the Gulf environment without a thorough analysis of accounting performance
4	The impact of digital transformation on the efficiency of accounting systems in Arab banks	Abdullah (2020)	Statement on the impact of digital transformation on the accuracy and speed of the accounting system	Technical improvements, but risks of weak oversight remain	Similarity in the link between technology and accounting systems	It did not detail the AI techniques or the nature of the risks.
5	Technological challenges in Iraqi banks	Hamid (2021)	Analysis of the reality of the technological infrastructure of Iraqi banks	Weak cybersecurity and a lack of technical skills	Match in the target environment (Iraq)	It did not directly address artificial intelligence or its accounting impact.

Table 2: Operationalization of Variables

Variable type	Variable name	Dimensions/Indicators	clarification
independent variable	Risks of artificial intelligence technologies	- Security risks - Algorithmic errors - Poor transparency - Technical glitches - Over-reliance on automation	Represents the threats that may arise from the use of artificial intelligence in accounting systems.
dependent variable	Accounting information systems performance	- Accuracy of information - Processing speed - Reliability - Operational efficiency - Quality of financial reports	It is measured by the extent to which the accounting system achieves its functions in supporting decision-making.
Intervening Variables	1. Efficiency of technological infrastructure 2. Level of human resource qualification 3. Degree of maturity of digital governance	- Providing secure devices and networks - Training and specialization in artificial intelligence - Existence of policies and controls to monitor smart systems	These variables affect the strength of the relationship between AI-induced risks and accounting system performance and may either weaken or strengthen this effect, depending on their levels within the bank.

The risks of artificial intelligence technologies and their impact on the performance of accounting information systems:

1- Introduction and General Framework : Accounting Information Systems (AIS) have undergone a qualitative transformation with the adoption of artificial intelligence (AI) technologies such as machine learning, natural language processing, software robots (RPA) , and generative models. This adoption has enhanced speed, reduced transaction costs, and improved the quality of predictive analytics. However, it has also introduced a wide range of technical, regulatory, ethical, and control risks that may directly affect the characteristics of accounting information and the overall performance of the system (accuracy, reliability, timeliness, relevance, auditability, security, and compliance) (Abed, Kareem et al. 2023).

This research aims to develop a comprehensive theoretical framework for classifying these risks, measuring their impact, and providing appropriate governance and mitigation controls within the accounting work environment (Boulianne, Fortin et al. 2023).

2- Basic concepts:

2:1-Accounting Information Systems (AIS): An integrated structure of human resources, procedures, databases, and technical applications for entering, processing, storing, and preparing financial and management reports, in accordance with the principles of measurement, recognition, and disclosure (Wani et al. 2024)

2:2- Artificial intelligence in accounting :A set of technologies that enable systems to learn from data and make semi-autonomous decisions or suggestions in accounting tasks (Rajput & Katamba, 2024), including:

Machine Learning (ML) Classification/Prediction Models for Estimates, Anomaly Detection, Cash Flow Forecasting, and Provision Estimation (Zwaid & Mohammed, 2025)

Natural Language Processing (NLP): Extracting data from contracts and invoices, summarizing disclosure notes, and linguistic assistance in preparing reports (Dasila, 2025)

Generative Artificial Intelligence (GenAI): Drafting disclosures, creating sensitivity scenarios, and generating explanations for indicators (Shon & Hou, 2025).

Software robots (RPA): Automation of recurring entries, reconciliation of account statements, and data migration between systems (González García & Álvarez-Fernández 2022).

Computer Vision: Reading invoices/receipts, Optical Document Recognition.

3- Drivers of adoption and the AI-powered accounting value chain

Motivations: Reducing account closing time, reducing entry errors, improving fraud detection, supporting analytical decisions, and reducing costs.(Assidi, Omran et al. 2025)

Value Chain: Data Collection → Cleaning and Validation → Processing/Recording → Financial and Management Reporting → Audit and Control.(Celestin 2024)

AI is in every loop: from intelligent data capture to continuous auditing /monitoring.

4- A comprehensive classification of artificial intelligence risks in accounting information systems.

4:1-Strategic and governance risks : Use cases not aligned with company objectives or disclosure strategy .Over-reliance on AI outputs rather than professional judgment.(Zwaid and Mohammed 2023)

4:2-Data Risk : Data Quality (Missing /Biased/Outdated .(Data sovereignty, privacy, and financial data sensitivity, Data Lineage and Poor Documentation..(Zhang, Wu et al. 2023)

4:3-Model Risk : Overfitting/Hallucination/Instability over time) Model Drift) Poor interpretability and difficulty in justifying accounting decisions to auditors .Lack of validation before publication..(Zakharkin, Myroshnychenko et al. 2024)

4:4- Compliance and Legal Risks : Conflict with privacy, data protection, and record retention legislation .Legal implications of relying on third-party models or cloud interfaces.(Shatskov 2024)

4:5- Information security risks : Attacks on models and data (data poisoning, model extraction) .Breaches affecting the integrity of records and general ledgers.(Ahmed and Al-Hamood 2024)

4:6-Operational and business continuity risks :system failures, automation line downtime, poor RPA integration with ERP, third-party and cloud model/service provider risks (Nambiar & Mundra 2022)

4:7- Human and ethical risks: Algorithmic biases that affect accounting estimates or tax decisions .Erosion of human competencies and separation of duties if roles are misallocated . Reputational risks from generative errors in disclosure (Saleh, Marei et al. 2023).

4:8- Audit and Evidence Risks: Difficulty in reproducing algorithmic logic or tracing the impact of a decision .Insufficient operating logs are not adequate and appropriate audit evidence (Igbekoyi et al., 2023).

5- Risk Map by Technology : Technology Key Risk Sources Examples in Accounting ML Data Quality/Bias, Drift, Poor Interpretation, Provision Estimation, Anomaly Detection in Entry .GenAI Hallucination, Data Confidentiality Violation, Misleading Wording Disclosure Drafts, Indicator Explanations, RPA Scenario Fragility, System Interface Changes, Entry Reconciliation, System Migration .Computer Vision OCR Accuracy, Low Quality Images Reading Invoices/Receipts and Accounting Proofreading (Liu & Fu, 2024).

6-The impact of risks on the dimensions of accounting information systems performance.

6:1- Accuracy and Reliability: Data/model risks may reduce the accuracy of entries and measurements, affecting the faithful representation of the financial position(Al-Worafi, 2024).

6:2- Timeliness: AI speeds up closing, but downtime or the need to retrain models can delay reporting (Myroshnychenko et al., 2024).

6:3- Relevance and Resolvability: Predictive models increase the relevance of information, but their bias can mislead estimates (Dasila, 2025).

6:4- Auditability and Transparency : Poor interpretability reduces auditor confidence and makes it difficult to trace the impact of a decision (Shen et al., 2025).

6:5- Efficiency and cost : Automating tasks reduces costs, while managing model lifecycles and continuous monitoring creates new costs that must be balanced (De Miguel & Sarasa-Cabezuelo 2025).

6:6- Security and confidentiality : Any breach directly affects the integrity of the records and the confidentiality of financial data (Dey et al., 2023).

6:7- Compliance : Compliance failures lead to fines, reputational risks, and reduced reporting quality.

7-Key Performance Indicators (KPIs): Account closing time (closing days before/after smart systems) (Kumar 2023).

Constraint error rate = number of corrections ÷ total constraints.

Cost of a single accounting transaction.

The percentage of restrictions automatically approved without intervention.

True Positive Rate.

Invoice/Contract Processing Time (Average in minutes/hour).

Policy compliance rate (control testing results) (Jamal et al., 2021)

Auditability (availability of complete operating records, percentage of reproducible cases).

8- Proposed risk management and governance framework

8:1- Governing Principles: Accountability and Clarity: Identify an owner for each model/process.

Transparency and explainability: Adopt models that are as explainable as possible, or provide an explanation layer (XAI).

Proportionality and risk: The more sensitive the accounting decision, the more stringent the controls.

Pre-Compliance : Pre-Deployment Privacy and Algorithmic Impact Assessment (PIA/AIA). (KaluvaKuri et al., 2021)

8:2- Supporting frames of reference

COSO for internal control ,COBIT for IT governance,

ISO/IEC 27001 for Information Security,

ISO/IEC 42001 (Artificial Intelligence Management Systems) is a comprehensive management framework. AI Ethics Policies (Fairness, Transparency, Accountability).(Kazakova, Shuvalova et al. 2020)

8:3- Controls across three layers: Data Controls: Quality Standards, Sensitivity Classification/Tagging, Origin Tracking, Access and Encryption Controls, Legal Retention. Model Risk Management: Methodology documentation, independent validation groups, bias/stability tests, Champion–Challenger baseline, ongoing performance monitoring, retraining plans, and prohibition on self-publishing without review(Ning et al., 2023).

Application and Operational Controls: Segregation of Duties, Automated Constraint Approvals, RPA Permission Limits, Detailed Operational Logs, Scenario Testing, and Disaster Recovery

8:4- Governance Roles: First line of defense: Accounting process owners and data/model teams.

Second line of defense: risk management, compliance, and information security.

Third line : Internal (and later external) audit to test controls and evidence (Wang et al., 2024).

9- Specific mitigation controls according to the risk category: Risk Category Potential Impact on Performance Mitigating Controls, Data Validation Rules, Periodic Human Samples, Drift Control, Approved Data Sources Policy, Model bias/hallucination Misreporting, false estimates Bias testing, feature documentatio XAI ,mandatory professional review before approving sensitive outputs Information Security Loss of Confidentiality/Integrity Constraints Encryption MFA ,Principle of Least Validity, Penetration Testing, Log Monitoring.(da Silva Brum, Solana-González et al. 2023).

PIA/AIA fines/reputation compliance ,record retention policies, legal review of supplier contracts, Operation RPA Processing Stop/Repeat Constraints Event-Driven Design No Screens, Regression Tests, Alternative Manual Processing Paths. Third Party Dependency/Disruption: Supplier Evaluation, Service Level Agreements, Data Export Controls, Exit Plans. Auditability Poor reliability/delayed closure Interpretation records, dated sample copies, intermediate output preservation, reproducible evidence(Solana González et al., 2023).

10- Considerations specific to the accounting environment: There is no substitute for professional **judgment :**Model results are auxiliary inputs, not final decisions on sensitive estimations (impairment, provisions, downside tests) (Solomon, 2023).

Compliance with standards : Measurement and recognition algorithms must comply with accounting standards, and differences must be documented (Schumacher & Beers, 2024).

Audit Evidence : The decision trace and sufficient explanation must be preserved to enable the auditor to re-implement or reach a reasonable degree of reassurance. (Fan & Guan, 2025).

Separation of development and operation :to prevent conflicts of interest and unauthorized modifications (Liu, Chen et al. 2022).

Disclosure Ethics : Prevent automated generation of sensitive text without human review; label any generated text (Zhou, Yu et al. 2020).

11- Methodology for measuring the impact on performance:

Phase 1 – Baseline: Measure KPIs before publishing (entry errors, close time, cost/transaction…).

Phase 2 – Controlled Experiment: Incremental A/B or Pilot deployment to selected operations.

Stage 3 – Continuous Monitoring: Dashboards that link model performance to accounting metrics (e.g., if the true anomaly rate increases, fraud detection improves).

Phase 4 – Periodic Reviews: Analyze performance deviations, audit controls, update data policies and models(Armenian 2022).

12- A Safe Practical Roadmap for Adopting AI in AIS: Identify use cases by impact/risk, Data flow diagram, classification, and storage/processing locations. Conduct a Privacy Impact Assessment and Algorithms (PIA/AIA). Choose models and techniques that are as interpretable as possible.

Prepare a documentation package for the model, including data, features, assumptions, and constraints. Establish publishing controls: independent review, approvals, segregation of duties (Lee and Lee 2024).

Manual Override: Design operating logs as audit evidence: inputs/outputs/model version/parameters/date**,** Train users and auditors to read model outputs and limitations**,** Monitor drift and model performance, with alarm thresholds and automatic shutdown**,** Clear agreements with third-party providers regarding security, sovereignty, and compliance**,** Periodic governance review at the Board of Directors/Audit Committee level (Araujo, Fort et al. 2024).

13- Risk Assessment Matrix Template (Abbreviated)

Probability :Low/Medium/High.

Impact :on accuracy/timeliness/compliance/security/cost.

Classification : Accept/Reduced/Converted/Avoided.

Risk Owner : Responsible function (Finance, IT, Risk).

Early warning indicators: high extraction errors, increasing manual exceptions, fluctuating accuracy metrics (Miller et al., 2024).

14- The role of internal and external audit

Internal Audit: Testing the design and operating effectiveness of controls, reviewing model documentation, data, and operating records, and re-implementation tests.

External Audit : Assessing the sufficiency of evidence generated by AI tools, verifying that algorithms do not conflict with accounting requirements and professional standards, and requesting disclosures about the use of AI when necessary(Pramukti, 2024).

15 - Ethical and societal challenges associated with accounting

Fairness and Non-Discrimination : Prevent biases in credit risk pricing or collection decisions that affect restrictions.

Transparency: Enable users and auditors to understand the overall logic of the output.

Accountability : Identifying who is responsible when an error or harm occurs as a result of a model.

The second section :the applied aspect of the research.

Table 3: Selection of banks and sample size

number	Bank name	the address	Sample number	comments
1	Central Bank of Iraq	Baghdad - Rashid Street	25	Employees from accounting departments
2	Rafidain Bank	Baghdad - Al-Jumhuriyah Street	20	Staff from the IT and accounting departments
3	Commercial Bank of Iraq	Baghdad - Abu Nuwas Street	20	Employees in the accounting department and the internal audit department
4	Development Bank of Iraq	Baghdad - Karrada District	15	Staff from the accounting and finance departments
5	Rafidain Bank Dhi Qar	Dhi Qar - University Street	20	Employees from the accounting and administrative departments

Total sample: 100 employees

Table 4: Stability Test

number	Distance	Number of items	Cronbach's Alpha	Interpretation
1	Information security risks	5	0.87	very high
2	Algorithmic Risks	4	0.83	very good
3	Poor transparency	3	0.79	good
4	Technical failures	3	0.81	very good
5	Accounting information systems performance	7	0.90	excellent

- note:
  - Values greater than 0.7 are generally accepted as evidence of instrument reliability.
  - Values above 0.8 mean high stability.

1. Descriptive analysis of demographic data

Table 5: Frequency distribution and percentages of demographic data for the study sample

variable	Category	repetition (n)	percentage (%)
Sex	male	62	62.0%
	feminine	38	38.0%
the age	less than 25	12	12.0%
	25-34	28	28.0%
	35-44	34	34.0%
	45-54	18	18.0%
	55 and over	8	8.0%
Academic qualification	diploma	7	7.0%
	Bachelor's	56	56.0%
	Master's	29	29.0%
	PhD	8	8.0%
Years of experience	Less than 3 years	11	11.0%
	3-5 years	21	21.0%
	6-10 years	39	39.0%
	More than 10 years	29	29.0%
Department	Information systems	26	26.0%
	accounting	33	33.0%
	Auditing	24	24.0%
	Management	17	17.0%

The results of the descriptive analysis of the sample data of 100 male and female employees using SPSS software showed that males constituted the majority at 62% compared to 38% of females, reflecting a good representation of both genders, with a relative dominance of males in the banking environment. As for the age group, the (35-44) category was the most represented at 34%, followed by the (25-34) category at 28%, indicating the dominance of young energies and intermediate experience among the cadres. Regarding educational qualifications, the bachelor's degree was the most common at 56%, followed by the master's degree at 29%, reflecting a high educational level among the sample members.

As for years of experience, 39% of respondents were concentrated in the 6–10-year category, indicating an experienced segment that is still in the process of professional development. Finally, the sample was distributed across different departments, with the accounting department accounting for the largest percentage (33%), followed by information systems (26%), auditing (24%), and finally management (17%). These results demonstrate the sample's diversity and balanced distribution, enhancing the study's credibility in measuring the impact of artificial intelligence technologies on accounting information systems across various functional perspectives.

Table 6: Descriptive analysis of questionnaire dimensions (n = 100)

Dimension	Number of items	arithmetic mean	standard deviation	Relative importance (%)	Arrangement
Information security risks	10	3.88	0.65	77.6%	2
Algorithmic and software risks	10	3.67	0.71	73.4%	4
Lack of transparency and oversight	10	3.59	0.74	71.8%	5
Technical failures and reliance on automation	10	3.93	0.60	78.6%	1
Accounting information systems performance	10	3.82	0.66	76.4%	3

The results of the descriptive analysis using SPSS showed that the dimension with the highest relative importance was "Technical Failures and Reliance on Automation," with a mean of 3.93 and a standard deviation of 0.60, reflecting employees' concerns about over-reliance on smart systems and the possibility of their sudden downtime. It was followed by " Information Security Risks," with a mean of 3.88 and a relative importance of 77.6%, indicating a high awareness among employees of the importance of cybersecurity in light of the use of artificial intelligence.

The performance of accounting information systems ranked third, with an average score of 3.82, indicating relative satisfaction with their performance, particularly regarding speed and accuracy. " Algorithmic and software risks " came in fourth place with a score of 73.4%, indicating awareness of the risks of inaccurate programming. The least-rated dimension was "weak transparency and oversight," with a score of 71.8%, reflecting a limited sense of a gap in oversight or in system clarity among some employees.

Overall, the results demonstrate a heightened awareness of the risks and impacts of AI, highlighting the importance of building resilient, secure, and transparent systems in the banking and accounting environment.

Hypothesis analysis

The first hypothesis (H1):

" There is a statistically significant relationship between the risks of artificial intelligence technologies and the performance of accounting information systems in banks."

Table 7: Pearson correlation coefficient between AI risks and accounting information systems performance

The two variables	Correlation coefficient (r)	Significance level (Sig.)
Risks of artificial intelligence technologies	0.656	0.000 (<0.01)
Accounting information systems performance		

The Pearson correlation coefficient test revealed a strong positive correlation between AI risks and the performance of accounting information systems. The correlation coefficient (r = 0.656) was statistically significant at the Sig. level. = 0.000 level, which is less than 0.01, indicating a highly significant relationship. This means that the greater the degree of awareness of individuals regarding the risks of AI technologies (such as cybersecurity, programming, and malfunctions), the more efficient and effective the performance of accounting information systems will be, resulting in improvements in governance and supervisory caution. This suggests that risks are an incentive for professional vigilance and continuous improvement, especially in sensitive financial environments such as banks.

Table 8: Simple regression analysis of AI risk as an independent variable and system performance as a dependent variable

The model	B (slope)	Std. Error	Beta (β)	t	Sig.
Constant	1.142	0.221	-	5.17	0.000
Risks of artificial intelligence	0.684	0.096	0.656	7.15	0.000

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The results of a simple regression analysis indicate that AI risks are a strong predictor of change in accounting information systems performance**.** The unstandardized regression coefficient (B) was approximately 0.684, indicating that each unit increase in AI risk perception is associated with a 0.684-unit improvement in accounting system performance. The t-value (t = 7.15) is statistically significant (Sig. = 0.000). This provides evidence of a clear causal relationship, as the model results indicate that organizations with a high degree of awareness of technical risks are better able to implement organizational measures that improve accounting performance.

Table 9: F- test for analysis of variance (ANOVA) for the regression model

Source	Sum of Squares (SS)	degrees of freedom (df)	Mean square (MS)	F	Sig.
decline	19,422	1	19,422	51.22	0.000
error	25,578	98	0.261		
Total	45,000	99			

(ANOVA) test confirms the validity of the regression model used, with an F value of 51.22, which is statistically significant at the Sig. = 0.000 level. This indicates that the independent variable (artificial intelligence risks) has a significant effect on the dependent variable (accounting information systems performance). This demonstrates that the observed variance in system performance is not random, but is largely attributable to variations in the level of perception of technical risks. This analysis enhances the strength and suitability of the model in scientifically explaining the studied relationship, and supports its reliance on it to guide management decisions in banks.

Table 10: Regression Model Summary

The model	**R**	**R^2**	**Modified R^2**	**Standard error of estimate**
1	0.656	0.430	0.424	0.511

The regression model summary shows that the coefficient of determination R^2, is 0.430**,** which means that 43% of the variation in accounting information systems performance can be explained by perceptions of AI-related risks. This reflects the model's good explanatory power. The adjusted R (0.424)also demonstrates the reliability of the results when generalized to the larger population. The standard error of the estimate (0.511) indicates that the differences between the actual and predicted values are within an acceptable level, which means that the predictive model is sufficiently accurate. This model reinforces the idea that informed management of AI risks can improve the performance of accounting systems in banks.

Table 11: Pearson correlation coefficients between risk dimensions and accounting system performance

Dimension	Correlation coefficient (r)	Sig. (2-tailed)
Information security risks	0.671	0.000
Software and algorithm risks	0.604	0.000
Lack of transparency and oversight	0.581	0.000
Technical failures and automation	0.693	0.000

Correlation analysis between the sub-dimensions of AI risks and accounting information systems performance showed that all dimensions had strong, statistically significant relationships with system performance. The strongest dimension was "Technical Failures and Automation " (r = 0.693), followed by "Information Security " (r = 0.671), indicating that concerns about system downtime or data disruption are the most significant contributors to performance efficiency. The relatively weakest (though still strong) correlation was with "Poor Transparency," indicating that, despite its importance, technical aspects have a greater impact on actual performance in a banking environment that relies on accuracy and speed.

The second hypothesis (H2):

' perceptions of the risks of AI technologies vary according to demographic variables (gender, educational qualification, department).

Table 12: T- Test for differences in risk perception by gender

Sex	number	arithmetic mean	standard deviation	T value	Sig. (2-tailed)
male	62	3.89	0.48	2.151	0.034
feminine	38	3.71	0.51		

t -test showed that there are statistically significant differences between males and females in their perception of the risks of artificial intelligence technologies, with a value of (t = 2.151) and a significance level of (Sig. = 0.034 < 0.05). This means that males are more aware of or more conservative about these risks than females. This is likely due to the nature of the technical tasks that males are more often assigned in the banking sector, or to differences in technical backgrounds. This difference calls for management's special attention in providing balanced training for both genders to unify their levels of understanding and preparedness to confront potential risks.

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Table 13: One-Way ANOVA test for the difference in risk perception according to academic qualification

Academic qualification	number	Average	standard deviation
diploma	7	3.60	0.45
Bachelor's	56	3.78	0.44
Master's	29	3.95	0.42
PhD	8	4.12	0.38
F -value		4,331	
Sig.			0.007

ANOVA test revealed a significant difference in employees' perceptions of AI risks based on academic qualifications, with F = 4.331 and Sig. = 0.007, which is less than 0.01, indicating that the differences are statistically significant. Individuals with higher degrees (Master's and PhD) demonstrated greater risk awareness, possibly due to their broader academic exposure to technology and digital governance topics. It is recommended that organizations take these differences into account when designing awareness and training programs to ensure awareness is raised even among those with lower qualifications.

Table 14 : ANOVA test for the difference in perception according to the administrative department

Department	number	arithmetic mean	standard deviation
Information systems	26	4.01	0.41
accounting	33	3.77	0.44
Auditing	24	3.68	0.48
Management	17	3.65	0.50
F		5,029	
Sig.			0.003

ANOVA test indicates significant differences between different departments in their perception of AI risks, with F = 5.029 and statistically significant (Sig. = 0.003). The Information Systems Department recorded the highest mean (4.01), which is logical given their direct work involvement with technical systems, making them more aware of potential risks. The administrative and accounting departments recorded lower means, reflecting differences in technical understanding of risks. The study recommends engaging all departments, especially non-technical ones, in training courses to enhance their ability to assess and understand the risks of modern technology.

Table 15 : **Post Hoc (Tukey) test for differences between academic qualifications**

comparison	The difference between the averages	Sig.
PhD - Bachelor's	0.34	0.016
Master's - Bachelor's	0.17	0.044
PhD - Diploma	0.52	0.005

Tukey test was conducted to determine the source of differences between the categories, based on the hypothesis related to educational qualifications. The results revealed significant differences between PhD holders and both bachelor's and diploma holders (Sig. < 0.05) ,with PhD holders showing a higher awareness of risks. Differences also emerged between master's and bachelor's degrees. This suggests that the higher an employee's educational level, the greater their awareness of AI risks. Therefore, banking institutions need to allocate intensive educational programs for employees with lower educational levels to ensure their strategic awareness is raised.

Table 16 : Levene's test for homogeneity of variance by gender

variable	Levene's Test	Sig.
Sex	3.872	0.052

Levene's test indicates that the variance of participants' responses to the risks of artificial intelligence does not differ significantly (Sig. = 0.052 > 0.05). This means that the assumption of homogeneity of variance between the two groups (males and females) is acceptable, supporting the validity of the t -test results presented previously. In other words, there is no bias in the variance of responses that could affect the outcome of the hypothesis, which enhances the reliability of the results and conclusions related to the difference in perception by gender. This test contributes to confirming the balance of the study sample and its lack of statistical bias.

3- Hypothesis (H3):

“Lack of transparency and oversight affects the efficiency of accounting information systems when using artificial intelligence in banks”

Table 17: Pearson correlation coefficient between weak transparency and the performance of accounting information systems

The two variables	**Correlation coefficient (r)**	**Sig. (2-tailed)**
Lack of transparency and oversight	0.581	0.000
Accounting information systems performance		

Pearson analysis results indicate a moderately strong, statistically significant positive correlation between weak transparency and oversight and the performance of accounting information systems, with the correlation coefficient (r = 0.581) at a significance level of (Sig. = 0.000). This means that the more employees perceive weak transparency and oversight, the more this negatively impacts the efficiency of the accounting system's performance, especially when integrating artificial intelligence technologies. This result highlights the importance of providing a clear and transparent oversight environment when adopting artificial intelligence in financial systems, to avoid a loss of trust and enhance the accuracy of financial operations and related decisions.

Table 18: Simple regression analysis between poor transparency (independent) and system performance (dependent)

The model	B (regression coefficient	Std. Error	Beta (β)	t	Sig.
Constant	1,390	0.225	-	6.18	0.000
Poor transparency	0.637	0.098	0.581	6.51	0.000

A simple regression analysis showed that weak transparency and oversight have a significant and direct impact on the performance efficiency of accounting information systems. The regression coefficient value (B = 0.637) means that every unit increase in weak transparency is accompanied by a 0.637 unit increase in system performance degradation. The t-value = 6.51 is statistically significant (Sig. = 0.000). This indicates that banking professionals recognize the importance of clear oversight and accountability mechanisms, and that the absence of such transparency weakens system performance, even when the technical tools are advanced. Therefore, digital governance is a critical factor in the success of artificial intelligence applications.

Table 19: ANOVA analysis of variance for the regression model

Source	Sum of Squares (SS)	df	Mean square (MS)	F	Sig.
decline	18,750	1	18,750	42.39	0.000
error	26,250	98	0.268		
Total	45,000	99			

(ANOVA) test confirmed the significance of the regression model between poor transparency and accounting information systems performance, with F = 42.39 at the significance level (Sig. = 0.000). This indicates that the statistical model used is valid for representing the relationship between the two variables, and that the effect of poor transparency on performance is not a result of randomness or individual variation, but rather a real and reliable effect. This highlights the importance of integrating oversight and transparency as essential elements within artificial intelligence systems, to prevent the latter from becoming a tool that widens the information gap or facilitates violations within banks.

Table 20: Regression Model Summary

The model	R	R²	Modified R²	Std. Error
1	0.581	0.338	0.331	0.518

The model summary results indicate that the coefficient of determination (R^2) was 0.338 , meaning that 33.8% of the variation in accounting information systems performance is explained by weak transparency and control. The adjusted R^2 was 0.331, reflecting the model's good stability even when generalized to similar societies. This ratio is significant in behavioral and field studies, and highlights the need to not rely solely on technology as a means of improving performance, but rather the need to create a transparent and organized administrative environment. The acceptable estimated standard deviation (0.518) indicates that the model's estimation errors are within the reasonable range, enhancing the credibility of the results.

Table 21: Correlation analysis between indicators of weak transparency and system performance

Item	r (link)	Sig.
Lack of internal control	0.561	0.000
Lack of clarity of responsibilities	0.573	0.000
Poor disclosure of updates	0.526	0.000
Limited accountability of systems	0.498	0.000

The table presents a sub-analysis of four indicators representing weak transparency and control. All indicators showed a statistically significant correlation with accounting information systems performance, with the highest correlation being with "unclarity of responsibilities " (r = 0.57, followed by "absence of internal control " (r = 0.561). This indicates that the absence of clear accountability structures and task allocation within the system is detrimental to performance efficiency, even in the presence of artificial intelligence. Financial institutions are recommended to incorporate transparency into programming, operation, and reporting to ensure that artificial intelligence is a performance enabler rather than a source of ambiguity or misinformation.

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Table 22: Summary of the general results of testing the study hypotheses

Hypothesis number	**Hypothesis text**	**Relationship type/difference**	**Statistical significance (Sig.)**	**Correlation/Impact Coefficient**	**Explanation ratio (R^2) or F**	**Overall result**
The first hypothesis (H1)	There is a statistically significant relationship between AI risks and the performance of accounting information systems.	strong positive association	0.000 (function)	r = 0.656 / β = 0.684	$R^2 = 0.430$	Acceptable - Strong and influential relationship
The second hypothesis (H2)	Employee perceptions of AI risks vary by gender, qualification, and administrative department	Statistically significant differences according to variables	Gender: 0.034			
Qualification: 0.007						
Section: 0.003	F between groups > 4 / T dal	-	Acceptable - There are significant differences			
Hypothesis 3 (H3)	Lack of transparency and oversight impacts the performance of accounting information systems in the context of the use of artificial intelligenc	Moderate positive effect	0.000 (function)	r = 0.581 / β = 0.637	$R^2 = 0.338$ / F = 42.39	Acceptable - Moderately significant effect

Conclusions

1- The study results showed significant and interconnected effects between the risks of artificial intelligence technologies and the performance of accounting information systems in Iraqi banks. The results of the first hypothesis revealed that employees' perceptions of artificial intelligence risks, such as security breaches, obscure algorithms, and technical failures, are positively related to improved accounting information system performance, with the correlation coefficient (r = 0.656) and the model explaining 43% of the variance in performance.

2-The results of the second hypothesis demonstrated the existence of statistically significant differences in employees' perceptions of technical risks based on gender, academic qualification, and administrative department, which reflects a difference in the cognitive and technical backgrounds that influence risk awareness.

3- The results of the third hypothesis showed that weak transparency and oversight are a factors influencing the system's performance efficiency. It was found that the greater the perception of a lack of governance and oversight, the lower the accounting system's performance, even with the use of artificial intelligence, with an explanation percentage of 33.8%. It was also found that the most influential indicators were the absence of internal oversight and the lack of clarity of responsibilities.

4- Together, these findings indicate that the adoption of AI technologies cannot be effective without a transparent and informed regulatory system, and that human knowledge and administrative organization remain essential foundations for the success of digital transformation in banking and accounting systems.

Recommendations

1-Strengthening awareness and continuous training programs: Iraqi banks should organize ongoing training courses and workshops to educate employees about the risks of artificial intelligence technologies, particularly for employees with different educational qualifications and in non-technical departments, to unify understanding of these risks and how to address them.

2-Developing IT governance and transparency frameworks: Banks must adopt clear and transparent policies for controlling information systems, including clear allocation of responsibilities, enhanced accountability, and the implementation of integrated oversight mechanisms that ensure data integrity and improve performance when using artificial intelligence.

3- Modernizing the technical infrastructure with a focus on cybersecurity: Investment should be made in modern technologies to enhance information security and provide effective tools for monitoring potential malfunctions and breaches, to ensure that accounting information systems are protected from technical risks that could affect the accuracy and efficiency of performance.

4- Encouraging a culture of innovation and continuous review: Banks should adopt a corporate culture that encourages innovation in the use of artificial intelligence technologies; while conducting periodic reviews of oversight and transparency systems to ensure they keep pace with technological developments and mitigate associated risks.

5- Integrating multidisciplinary teams in risk management: It is recommended to form teams of employees with technical, administrative, and accounting backgrounds to comprehensively assess risks and manage information systems effectively, ensuring a balance between the technical aspect and administrative governance

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