

Modelling audit risk with AI and explainability: Cross-country evidence from emerging and mature markets

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Abstract. This study examines how artificial intelligence (AI) compares with traditional econometric models in predicting audit risk across two institutional contexts: the United Arab Emirates (UAE) and the United Kingdom (UK). Using firm-level data from 2017–2024, audit risk is modelled using financial, governance, audit, and market factors. Logistic and probit regressions serve as econometric benchmarks, while Random Forest, XGBoost, and deep neural networks represent AI methods. Explainable AI (XAI) tools—such as SHAP and LIME—enhance interpretability and regulatory transparency. Findings show that AI models consistently outperform econometric ones in accuracy, recall, and AUC across both countries. Yet, key audit risk drivers vary: governance factors like board independence and ownership concentration dominate in the UAE, while financial indicators and Big 4 affiliation are more influential in the UK. Explainability tools clarify predictions, boosting trust and regulatory alignment. Cross-country transferability tests reveal lower accuracy outside the original setting, emphasizing institutional specificity. Overall, the study demonstrates that effective audit risk prediction requires locally adapted, transparent AI models that combine predictive strength with interpretability to enhance auditor and regulator confidence.

Keywords: Audit risk; artificial intelligence; explainable AI; comparative study; UAE; UK.

1. INTRODUCTION

Audit risk, defined as the probability that an auditor issues an inappropriate opinion when financial statements contain misstatements, has long been a central concern in accounting research (Perry et al., 2025). Traditional modelling approaches, including logistic regression and probit, remain widely applied because of their transparency and simplicity (Zhong et al., 2024). Yet their limitations have been repeatedly documented: they assume linearity, rely heavily on historical data, and often underperform when risk factors interact dynamically or shift under new conditions (Arsyad et al., 2025). These challenges are particularly visible in different institutional settings. The UAE, an emerging economy that has adopted IFRS and promoted AI-driven reforms, represents a fast-evolving audit environment with concentrated ownership and developing governance systems (Bader et al., 2025). In contrast, the UK provides a mature, highly regulated market, yet one still marked by high-profile audit failures such as Carillion, which exposed weaknesses in oversight and accountability (Lisina et al., 2024).

Despite extensive research, gaps remain. First, studies have primarily relied on econometric models, which fail to capture the non-linear and high-dimensional nature of audit risk (Morshed, 2024). Second, while AI techniques are increasingly applied in other financial domains, their integration into audit risk modelling is limited and often prioritises predictive accuracy at the expense of interpretability (Morshed, 2025). Third, most research is country-specific, leaving unanswered whether audit risk models generalise across different regulatory and institutional contexts (Alharasis et al., 2024).

Against this background, the study is guided by the following research questions:

RQ1. Do AI-based models predict audit risk more accurately than traditional econometric approaches in both the UAE and the UK?

RQ2. How do the most influential audit risk drivers differ between the UAE and the UK because of variations in institutional and regulatory environments?

RQ3. How do explainable AI techniques, particularly SHAP and LIME, enhance interpretability and trust in AI-driven audit risk models across both contexts?

RQ4. To what extent do AI models trained in one country lose predictive performance when applied to another, indicating context-specificity in audit risk determinants?

The research addresses these questions by combining econometric benchmarks with AI models (Random Forest, XGBoost, neural networks) and embedding SHAP and LIME to enhance interpretability. Using a comparative dataset from UAE and UK listed firms (2017–2024), the study fills methodological and contextual gaps by providing systematic evidence across two contrasting environments.

The contribution is threefold. It demonstrates the superiority of AI over econometric models, embeds explainability into audit risk frameworks, and offers rare comparative evidence of how institutional differences shape audit risk determinants.

The paper is structured as follows. Section 2 reviews the literature and develops the research questions. Section 3 explains the research methodology. Section 4 presents the findings according to the research questions. Section 5 discusses the results, and Section 6 concludes the study by outlining limitations, implications, and future research directions.

2. LITERATURE REVIEW

2.1. Audit risk in accounting research

Audit risk refers to the probability that an auditor expresses an inappropriate opinion when financial statements contain material misstatements. It is traditionally conceptualized through the audit risk model, which decomposes overall risk into inherent risk, control risk, and detection risk (Perry et al., 2025). This model provides the theoretical foundation for audit planning and evidence gathering, making risk assessment a cornerstone of both audit practice and research.

Early studies relied on judgmental assessments and regression-based models to link audit risk to firm-level characteristics such as leverage, profitability, auditor size, and governance quality (Tumewang et al., 2025). Outcomes such as qualified opinions, restatements, or fraud revelations were commonly used as proxies. While these approaches advanced understanding, they generally assumed stable and linear relationships, often overlooking the complex interplay among financial, governance, and market factors.

The limitations of such models became more apparent in light of high-profile audit failures (e.g., Enron, Carillion) and the increasing complexity of financial reporting. Globalization of auditing standards and the introduction of IFRS further expanded the scope of variables influencing audit outcomes. Moreover, modern business

environments generate large, diverse, and rapidly evolving datasets, challenging the adequacy of traditional risk models (Haapamäki & Mäki, 2024).

Consequently, recent literature highlights the need for more dynamic, data-driven approaches that can capture non-linear interactions and adapt to evolving conditions. This shift has opened the door for integrating advanced technologies such as machine learning and artificial intelligence into audit risk modelling, a focus increasingly emphasized in contemporary research.

2.2. Traditional modelling approaches

Traditional approaches to modelling audit risk have relied primarily on statistical and econometric methods, most notably logistic regression, probit models, and discriminant analysis. These methods use financial ratios, audit firm characteristics, and governance indicators to predict outcomes such as qualified audit opinions, restatements, or fraud incidence (Zhong et al., 2024). Their popularity stems from their interpretability and ease of application, which align with the audit profession's emphasis on transparency and accountability.

Despite their contributions, these models face important limitations. First, they often assume linearity and independence among predictors, overlooking complex and interactive relationships between audit risk factors. Second, they are generally static, relying on historical data and unable to adapt quickly to new economic or regulatory conditions (Arsyad et al., 2025). Third, their predictive power weakens in high-dimensional settings where multiple risk factors interact in non-linear ways, such as during periods of financial crisis or regulatory reform (Alsmadi & Alrawashdeh, 2025).

Evidence from both developed and emerging markets confirms these weaknesses. For instance, models based solely on financial ratios tend to underperform when governance variables or auditor characteristics play a stronger role (Wang & Guedes, 2025). Similarly, traditional models applied in emerging economies often face data quality and disclosure limitations, reducing their reliability compared to results from mature markets (Ramadan & Morshed, 2024).

As a result, while econometric approaches remain useful benchmarks, the literature increasingly acknowledges the need for more flexible, adaptive, and non-linear modelling techniques to capture the full complexity of audit risk. This recognition has motivated the rise of AI-based methods in contemporary audit research.

2.3. Advanced technologies in audit and accounting

The integration of advanced technologies has transformed how audit and accounting research approaches risk assessment and fraud detection. Techniques such as machine learning, artificial intelligence (AI), and big data analytics are increasingly used to model audit risk, predict anomalies, and improve decision-making. Unlike traditional econometric methods, these tools can capture non-linear interactions, high-dimensional data, and hidden patterns that are often missed by linear models (Shaban & Barakat, 2023).

Applications of AI in auditing include fraud detection systems, going-concern prediction, audit fee estimation, and risk scoring models. For example, ensemble methods such as Random Forest and XGBoost improve predictive accuracy by iteratively refining model performance, while deep neural networks allow the processing of large, unstructured data such as textual disclosures and social media sentiment (Qatawneh, 2025). Big data analytics has also enhanced auditors' ability to process continuous streams of transactional data, shifting risk assessment from periodic to near real-time monitoring (Abdelwahed et al., 2025). While deep neural networks can incorporate unstructured text in principle, the present study applies DNNs to structured firm-year variables (financial ratios, governance indicators, audit characteristics, and market controls); text-based disclosure features are proposed as a next step in future research.

Despite these advantages, challenges remain. AI models often function as “black boxes”, limiting interpretability and raising concerns about audit transparency, regulatory acceptance, and trust among stakeholders (Hassija et al., 2024). Moreover, data quality, availability, and consistency—particularly in emerging markets—can constrain the effective use of advanced technologies (Shaban & Omoush, 2025).

Overall, the literature shows that advanced technologies offer superior predictive capabilities and the potential to reshape audit practice. Yet, their adoption requires balancing accuracy with explainability and accountability, creating space for frameworks that integrate AI with transparent risk assessment approaches.

2.4. Explainable AI and audit transparency

While advanced AI models enhance predictive accuracy in audit research, their adoption is often constrained by the opacity of decision processes. In auditing,

transparency is critical: regulators, investors, and practitioners require not only reliable outputs but also an understanding of why a model produces a given prediction. This has prompted growing attention to explainable AI (XAI), which seeks to make complex algorithms interpretable without sacrificing performance (Sachan & Liu, 2024).

Two methods are particularly relevant to audit applications. SHAP (Shapley Additive Explanations) quantifies the contribution of each variable to a prediction, offering global insights into which financial, governance, or audit characteristics drive risk assessments (Gebreyesus et al., 2024). LIME (Local Interpretable Model-Agnostic Explanations) provides case-level interpretability, showing why a specific firm was classified as high-risk. Together, these tools allow auditors to reconcile sophisticated AI outputs with professional judgment and regulatory expectations (Shakir et al., 2024).

Literature highlights the dual benefits of explainability. First, it enhances trust and accountability, which are essential in audit environments where professional scepticism and verification are central (Al-Omush et al., 2025). Second, it facilitates regulatory compliance, as oversight bodies increasingly demand clarity in risk assessment methodologies (Othman, 2025). However, challenges remain, including potential oversimplification of complex models and the risk of misinterpreting explanatory outputs (Morshed, 2026).

In sum, explainable AI offers a pathway to bridge methodological sophistication with practical usability. It allows auditors and regulators to harness the predictive power of advanced models while maintaining transparency, credibility, and ethical accountability in audit decision-making.

2.5. Cross-country and institutional contexts

Audit risk modelling is strongly shaped by the institutional and regulatory environment, making cross-country analysis essential. The United Arab Emirates (UAE) represents an emerging market context where auditing practices have evolved rapidly alongside economic diversification. The UAE has fully adopted IFRS, strengthened corporate governance codes, and launched national strategies promoting digitalisation and AI adoption. Yet, challenges such as concentrated ownership structures, limited disclosure depth, and varying enforcement

mechanisms influence how audit risk is manifested and detected (Alharasis et al., 2024; Algrady et al., 2025).

By contrast, the United Kingdom (UK) offers a mature audit environment with long-established regulation under the Financial Reporting Council (FRC). Despite its sophistication, the UK has witnessed high-profile audit failures, including Carillion and Patisserie Valerie, which triggered reforms to strengthen audit quality, independence, and accountability (Lisina et al., 2024). The UK context also provides richer datasets and greater transparency, enabling robust modelling of audit risk factors.

Comparing these contexts highlights how institutional maturity and regulatory enforcement shape both the drivers of audit risk and the effectiveness of modelling approaches. In the UAE, governance variables such as board independence or audit committee expertise may carry disproportionate weight, while in the UK financial ratios and audit market dynamics are often more influential (Taqa, 2025).

An explicit Institutional theory lens helps explain this divergence. In emerging markets, institutional arrangements are often characterised by stronger ownership concentration, more uneven enforcement, and evolving professional norms, which increases the salience of governance mechanisms as signals of credibility and as substitutes for weaker external monitoring. By contrast, in mature markets with comparatively stronger regulative oversight, more established audit infrastructures, and denser normative pressures, baseline governance practices tend to be more standardised, so variation in financial performance and audit-market dynamics becomes more decisive in distinguishing risk.

Existing literature rarely integrates such comparative perspectives, focusing instead on single-country analyses. A UAE–UK comparison thus offers valuable insights into whether AI-based audit risk models generalise across institutional settings, and how contextual differences condition their performance and interpretability (Alharasis et al., 2024).

2.6. Research gap and research questions

Although audit risk has been widely examined, three major gaps remain unresolved. First, most studies rely on traditional econometric models such as logistic regression and probit. These models are interpretable but limited to linear, stable relationships and often fail to capture the complex interactions among financial,

governance, and market variables. By contrast, AI-based approaches can accommodate non-linearities and high-dimensional data, yet their application to audit risk is still underdeveloped, particularly in comparative settings (Bertozzi et al., 2024).

Second, existing AI-focused studies tend to privilege predictive accuracy over transparency. The absence of explainable AI in audit risk modelling reduces trust and restricts regulatory acceptance. While tools such as SHAP and LIME are increasingly used in other financial domains, their systematic application to audit risk remains scarce, creating a methodological gap between accuracy and interpretability.

Third, the literature is largely country-bound, with most evidence drawn from mature markets. Research in emerging economies is limited, and few studies assess whether AI models are generalizable across institutional contexts. The UAE provides an emerging setting with rapid regulatory reforms, IFRS adoption, and national AI strategies, while the UK represents a mature market with established oversight but recurring audit failures. This contrast raises an important unanswered question: are AI-based audit risk models globally transferable, or are they conditioned by institutional and regulatory environments?

By addressing these gaps, this study advances the literature in three ways. First, it integrates traditional and AI models to evaluate relative performance. Second, it embeds explainable AI to balance predictive power with interpretability. Third, it provides a comparative UAE–UK analysis, offering new insights into whether audit risk drivers are universal or context-specific.

From these gaps and contributions, and as illustrated in Figure 1, the research questions are organized around predictive performance, cross-country determinants, explainability, and transferability:

RQ1. Do AI-based models predict audit risk more accurately than traditional econometric approaches in both the UAE and the UK?

RQ2. How do the most influential audit risk drivers differ between the UAE and the UK because of variations in institutional and regulatory environments?

RQ3. How do SHAP and LIME enhance interpretability and trust in AI-driven audit risk models across both contexts?

RQ4. To what extent do AI models trained in one country lose predictive performance when applied to the other?

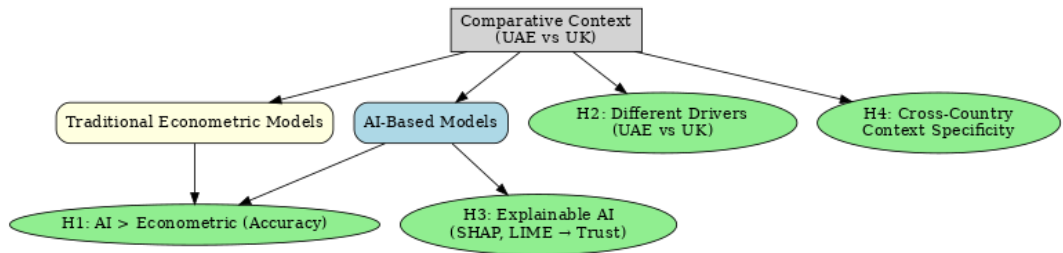


Figure 1. Conceptual framework

Source: Authors' elaboration

3. RESEARCH METHODOLOGY

3.1. Research Design

This study uses a comparative quantitative design to model audit risk in two institutional contexts, the UAE and the UK. It follows the antecedents–modelling–consequences framework: antecedents are financial, governance, audit, and market variables; modelling applies both econometric and AI methods; and consequences focus on improved predictive accuracy and managerial insights.

The dataset spans 2017–2024, covering major regulatory shifts (IFRS 9, 15, 16), the COVID-19 period, and recent audit reforms. This period ensures both depth and contemporary relevance.

A cross-country comparison strengthens generalizability. The UAE represents an emerging audit market with rapid reforms, AI policy support, and a strengthened framework for regulating the accounting and auditing profession (United Arab Emirates, 2023), while the UK reflects a mature system under FRC oversight, yet still marked by notable audit failures. This contrast enables testing AI robustness and identifying context-specific risk drivers.

By combining traditional benchmarks with AI and explainable tools (e.g., SHAP, LIME), the design enhances methodological rigor while ensuring results remain interpretable for auditors, regulators, and managers (Sithakoul et al., 2024).

3.2. Data collection

The study uses archival data from listed firms in the UAE and UK. For the UAE, information was drawn from annual reports and audit disclosures available on the Abu Dhabi Securities Exchange (ADX) and Dubai Financial Market (DFM). For the UK, data were obtained from Audit Analytics, the FAME database, Companies House filings, and Financial Reporting Council (FRC) reports (Abubakr et al., 2025; Liew et al., 2022).

The period 2017–2024 was selected to capture major regulatory changes (IFRS 9, 15, and 16), the impact of COVID-19 on financial reporting, and subsequent audit reforms. This timeframe provides sufficient variation to test the robustness of audit risk models under dynamic conditions.

The sample comprises around 300–350 firms per country, representing finance, manufacturing, energy, and services. Firms with incomplete audit or governance data were excluded. Both active and delisted firms during the period were considered to reduce survivorship bias.

The dependent variable is audit risk, measured through qualified opinions, financial restatements, and fraud-related flags. The independent variables include financial variables (leverage, profitability, and liquidity), governance variables (board independence, ownership concentration, and audit committee expertise), audit variables (Big 4 status, audit fees, and auditor tenure), and market variables (sector classification and stock volatility).

Data were cleaned through standardization, winsorization at 1% and 99% levels, and imputation of missing firm-year values. This balanced dataset provides a solid basis for comparative modelling across emerging and mature audit environments (Wu et al., 2024).

3.3. Modelling framework

The study applies a hybrid modelling framework to compare traditional econometric approaches with advanced AI methods in assessing audit risk. This design enables evaluation of both predictive gains and interpretability (Gafsi, 2025).

Traditional econometric techniques, namely logistic regression and probit analysis, serve as benchmark models. Three AI techniques are then implemented: Random

Forest, XGBoost, and deep neural networks. Random Forest is suitable for modelling non-linear patterns and ranking variable importance; XGBoost improves predictive accuracy through iterative boosting and regularization; and deep neural networks capture complex higher-order relationships across financial, governance, and audit variables.

To address black-box concerns, SHAP values provide global feature-importance evidence, while LIME offers local interpretability for individual firm-level predictions. This framework ensures that the models not only maximize predictive performance but also generate transparent and actionable insights for auditors, regulators, and managers.

3.4. Model training and validation

The modelling process followed four main stages. First, all variables were standardized, outliers were winsorized at the 1% and 99% levels, and missing values were imputed using firm-year averages. Categorical factors, such as sector classification and audit firm type, were converted into dummy variables (Mohamed et al., 2025).

Each country dataset was divided into a 70% training set and a 30% testing set. This split allows the models to be calibrated on sufficient data while preserving an independent subset for out-of-sample validation (Thapa et al., 2021).

To assess transferability, models trained on UAE data were tested on UK firms, and vice versa. This procedure evaluates whether AI models generalize across different institutional and regulatory settings (Oreqat, 2021).

Model performance was assessed using multiple indicators: accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC). These metrics capture both overall correctness and sensitivity to high-risk cases (Sukma & Namahoot, 2025).

Robustness was verified through alternative proxies of audit risk, sector-specific subsamples, and rolling-window tests comparing pre- and post-COVID periods (2017–2020 vs. 2021–2024).

This validation strategy ensures that the results are both statistically reliable and contextually relevant across emerging and mature audit markets (Morshed, 2025).

3.5. Comparative analysis

The comparative stage evaluates how audit risk is modelled across the UAE and UK. Three layers of analysis are conducted (Riskiyadi, 2024).

Within each country, the predictive performance of AI models is compared with traditional econometric benchmarks. Between countries, model outputs are contrasted across the UAE and the UK to identify differences in predictive accuracy, variable importance, and risk factor sensitivity. Cross-country validation then applies models trained in one country to the other, testing the generalizability of AI-driven audit risk models and revealing whether predictive patterns are context-specific or transferable.

The combined approach provides a systematic evaluation of both methodological performance and institutional effects, emphasis on linking modelling to managerial and policy implications.

3.6. Ethical considerations

The study relies exclusively on publicly available secondary data, such as annual reports, audit disclosures, and regulatory filings. As no human participants are involved, the research does not require formal ethical clearance.

Data handling follows the General Data Protection Regulation (GDPR) in the UK and applicable privacy provisions in the UAE. Company identifiers are used only for analytical purposes and are not disclosed in the results.

In line with Emerald's authorship and AI guidelines, all modelling techniques, software tools, and explainability methods are transparently reported. AI is applied strictly as an analytical tool, with full responsibility for interpretation retained by the authors.

Beyond privacy compliance, automated risk scoring raises issues of fairness, accountability, and professional judgment. Audit-risk labels and enforcement-related outcomes can embed detection and reporting biases that vary by sector and jurisdiction, which may lead to systematically higher scores for certain industries even when underlying risk is comparable. Accordingly, AI-based risk tools should be treated as decision-support rather than decision-replacement: interpretations should be documented, challenged through professional skepticism, and complemented with sensitivity checks (e.g., sector-level performance diagnostics

and calibration tests). Finally, to safeguard auditor independence, the governance of AI tools should ensure clear responsibility for model validation, avoid undue client influence on model settings, and maintain transparency over any third-party analytics providers used in engagements.

This ensures the study meets accepted ethical, legal, and professional standards while maintaining transparency and replicability (Dhou & Orudzheva, 2025).

4. FINDINGS

4.1. Preliminary descriptive statistics and correlations

Table 1 shows clear contrasts. UK firms are larger, more profitable, and less leveraged than UAE firms. Governance quality is stronger in the UK, with higher board independence and lower ownership concentration, while UAE firms rely more on concentrated ownership structures. Big 4 auditor coverage is higher in the UK, and auditor tenure is longer.

Variable	UAE Mean	UAE SD	UK Mean	UK SD
Firm Size (Assets, \$bn)	5.2	2.4	12.5	6.1
Market Capitalization (\$bn)	3.8	1.9	10.4	4.7
Leverage (Debt/Assets)	0.62	0.15	0.49	0.12
Profitability (ROA, %)	4.1	3.2	6.8	2.5
Liquidity (Current Ratio)	1.45	0.40	1.52	0.35
Board Independence (%)	41	12	61	11
Ownership Concentration (%)	48	18	29	14
Big 4 Auditor (%)	63	15	84	10
Audit Fees (\$m)	1.2	0.6	2.6	1.1
Auditor Tenure (Years)	5.8	2.3	8.4	3.1

Table 1. Descriptive statistics (UAE vs UK, 2017–2024)

Source: Authors’ elaboration

Correlation analysis (Tables 2 and 3) shows differences. In the UAE, governance variables (board independence, ownership concentration) are more strongly linked to audit outcomes. In the UK, financial ratios such as profitability and leverage dominate. Correlations remain moderate, minimizing multicollinearity concerns (Algrady et al., 2025).

Variable	Lev	Prof	Liq	Board Indep.	Own. Conc.
Leverage	1.00	-0.42	-0.25	-0.31	0.47
Profitability	-0.42	1.00	0.38	0.29	-0.22
Liquidity	-0.25	0.38	1.00	0.21	-0.18
Board Independence	-0.31	0.29	0.21	1.00	-0.44
Ownership Concentration	0.47	-0.22	-0.18	-0.44	1.00

Table 2. Correlation matrix – UAE

Source: Authors’ elaboration

Variable	Lev	Prof	Liq	Board Indep.	Own. Conc.
Leverage	1.00	-0.36	-0.28	-0.19	0.22
Profitability	-0.36	1.00	0.41	0.33	-0.15
Liquidity	-0.28	0.41	1.00	0.26	-0.20
Board Independence	-0.19	0.33	0.26	1.00	-0.31
Ownership Concentration	0.22	-0.15	-0.20	-0.31	1.00

Table 3. Correlation matrix – UK

Source: Authors' elaboration

4.2. RQ1 – Predictive performance of AI versus econometric models

RQ1 asks whether AI-based models predict audit risk more accurately than traditional econometric approaches in both the UAE and the UK.

Table 4 reports the results from logistic regression models predicting audit risk in UAE and UK firms. As expected, the explanatory variables differ across contexts. In the UAE, board independence and ownership concentration are significant, highlighting the role of governance structures. Leverage also shows a positive association with audit risk. In the UK, profitability and Big 4 auditor status are stronger predictors, while leverage remains significant but weaker than in the UAE.

These baseline results illustrate two patterns. First, econometric models capture some relevant relationships but achieve only moderate explanatory power. Second, the relative importance of predictors differs between the two institutional settings, suggesting that audit risk drivers are context-dependent. These findings set the stage for testing whether AI models offer stronger predictive accuracy and adaptability (Rane et al., 2024).

Variable	UAE Coefficient (p-value)	UK Coefficient (p-value)
Leverage	0.42*** (0.001)	0.21** (0.030)
Profitability (ROA)	-0.15 (0.112)	-0.28*** (0.005)
Liquidity	-0.07 (0.254)	-0.04 (0.412)
Board Independence	-0.33** (0.022)	-0.08 (0.318)
Ownership Concentration	0.37*** (0.009)	0.12 (0.206)
Big 4 Auditor (dummy)	-0.19 (0.141)	-0.35** (0.019)
Audit Fees	-0.11 (0.288)	-0.09 (0.242)
Auditor Tenure	0.06 (0.317)	0.04 (0.381)
Constant	-1.22** (0.018)	-0.94** (0.027)
Pseudo R ²	0.27	0.31
Observations	1,950	2,400

Table 4. Logistic regression results for audit risk (UAE vs UK)

Source: Authors' elaboration

Note: *** p < 0.01; ** p < 0.05; * p < 0.10.

AI models substantially improve predictive accuracy over the econometric benchmarks. Table 5 reports results for Random Forest, XGBoost, and Deep Neural Networks. Across both countries, AI models achieve higher accuracy, recall, and AUC, confirming their strength in capturing complex risk patterns (Table 5, Figure 2).

For the UAE, Random Forest performs best, with an AUC of 0.87, indicating strong classification of high-risk firms. In the UK, XGBoost yields the highest accuracy (0.86) and recall (0.81), reflecting its advantage in mature datasets. Deep Neural Networks also perform well but require larger samples for optimal performance (Pu et al., 2022).

Overall, these results support the view that AI outperforms traditional econometric models, but performance differs slightly by country, foreshadowing context-specific findings in later sections (Zheng et al., 2024).

Model	Accuracy (UAE)	Recall (UAE)	AUC (UAE)	Accuracy (UK)	Recall (UK)	AUC (UK)
Logistic Regression	0.71	0.64	0.72	0.74	0.67	0.75
Random Forest	0.83	0.78	0.87	0.84	0.76	0.85
XGBoost	0.82	0.75	0.85	0.86	0.81	0.88
Deep Neural Network	0.80	0.72	0.84	0.83	0.77	0.86

Table 5. Performance metrics of AI vs econometric models (UAE and UK)

Source: Authors' elaboration

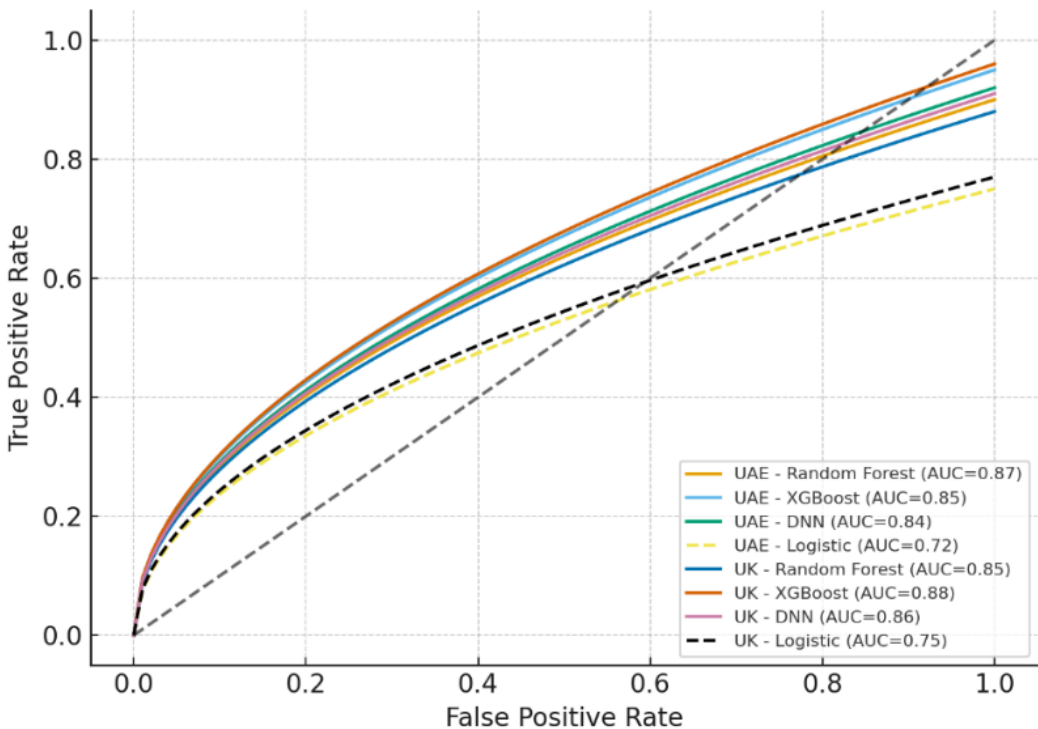


Figure 2. ROC curves, UAE vs UK models

Source: Authors' elaboration

4.3. RQ2 – Cross-country differences in audit risk drivers

RQ2 asks how the most influential audit risk drivers differ between the UAE and the UK because of variations in institutional and regulatory environments (Al-Muntasir, 2022).

To address interpretability, SHAP values were used to identify the most influential drivers of audit risk in both UAE and UK samples. Table 6 presents the top-ranked features. In the UAE, ownership concentration and board independence emerge as the strongest predictors, reinforcing the role of governance in an emerging market. In the UK, profitability and Big 4 auditor status dominate, consistent with stronger institutional oversight and disclosure (Table 6, Figure 3, Figure 4).

Rank	UAE (Emerging Market)	UK (Mature Market)
1	Ownership Concentration (+)	Profitability (-)
2	Board Independence (-)	Big 4 Auditor (-)
3	Leverage (+)	Leverage (+)
4	Audit Fees (-)	Auditor Tenure (-/weak)
5	Profitability (-/weak)	Liquidity (-)

Table 6. Top 5 SHAP-ranked features of audit risk prediction

Source: Authors' elaboration

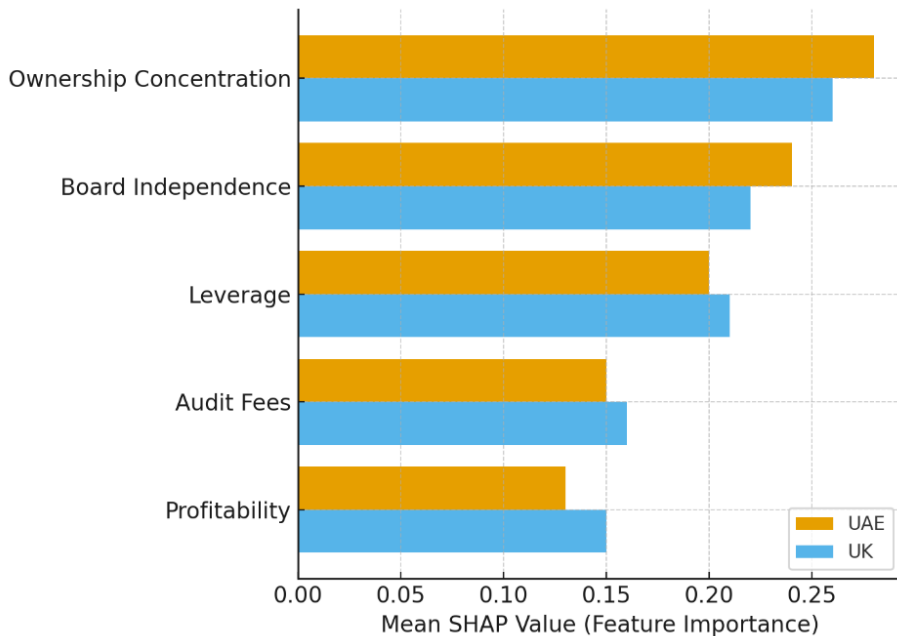


Figure 3. SHAP feature importance for audit risk (UAE vs UK)

Source: Authors' elaboration

This figure compares the average SHAP values for the top five features driving audit risk predictions in UAE and UK firms. Governance variables dominate in the UAE, while financial indicators and audit firm type are more important in the UK.

4.4. RQ3 – Explainability and transparency

RQ3 asks how explainable AI techniques enhance interpretability and trust in AI-driven audit risk models across the two contexts.

LIME explanations further confirm these patterns. For high-risk UAE firms, governance weaknesses (low board independence, high ownership concentration) significantly increased predicted audit risk. In UK firms, adverse financial indicators (declining profitability, high leverage) triggered higher risk scores, while Big 4 affiliation reduced them (Chen et al., 2023).

These results highlight that AI models not only improve predictive accuracy but also provide transparent insights into the variables driving audit risk across contexts. The findings suggest that audit risk determinants are shaped by institutional environments, with governance critical in the UAE and financial performance central in the UK (Abu Huson et al., 2025).

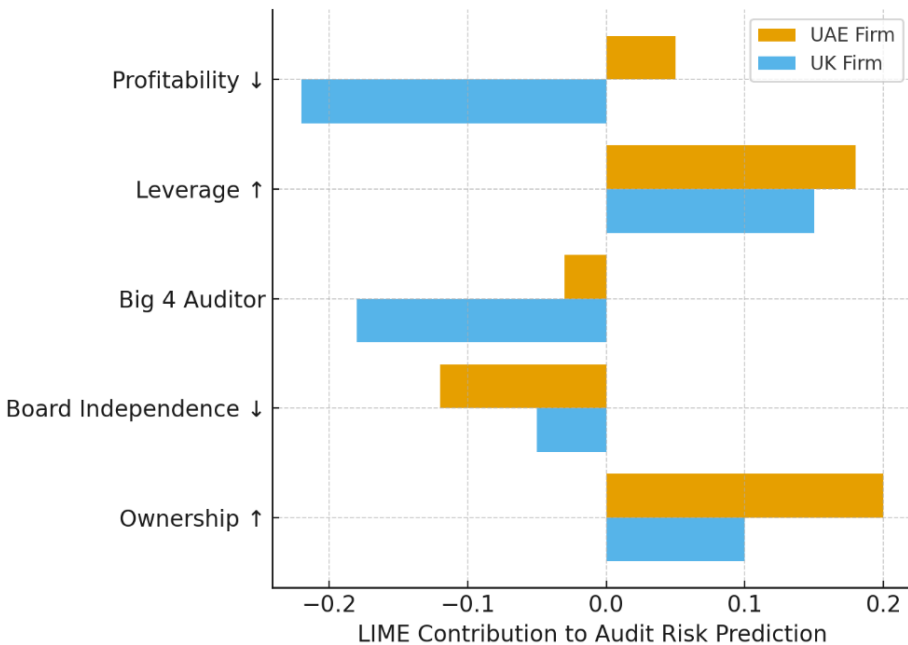


Figure 4. LIME explanations for individual firm cases (UAE vs UK)

Source: Authors' elaboration

This figure illustrates how specific factors contributed to the audit risk prediction for one UAE firm and one UK firm. In the UAE case, high ownership concentration and low board independence increased predicted risk, while in the UK case declining profitability and high leverage were decisive.

4.5. RQ4 – Cross-country transferability

RQ4 asks whether AI models trained in one country lose predictive performance when applied to the other country.

The cross-country analysis highlights both similarities and divergences in audit risk modelling. AI models consistently outperform traditional benchmarks in both settings, but the drivers of risk differ. In the UAE, governance factors—especially ownership concentration and board independence—carry greater weight (Srairi, 2025). In the UK, profitability and Big 4 auditor affiliation dominate, reflecting stronger institutional oversight (Mattar et al., 2024).

Transferability tests show a decline in predictive accuracy when models trained in one country are applied to the other (Table 7). For instance, the UAE-trained Random Forest model achieves an AUC of 0.87 within-sample but drops to 0.78 when applied to UK firms. Conversely, the UK-trained XGBoost model falls from an AUC of 0.88 to 0.80 in the UAE context (Ahmad et al., 2023). These results confirm that audit risk determinants are partly context-specific, shaped by institutional maturity, regulatory frameworks, and market practices. Overall, the findings suggest that while AI improves predictive modelling universally, customisation to institutional environments remains necessary for optimal performance (Hemachandran et al., 2022).

Model	UAE (in-sample)	UAE → UK	UK (in-sample)	UK → UAE
Logistic Regression	0.72	0.68	0.75	0.70
Random Forest	0.87	0.78	0.85	0.79
XGBoost	0.85	0.77	0.88	0.80
Deep Neural Net	0.84	0.76	0.86	0.78

Table 7. Cross-country model transferability results (AUC values)

Source: Authors' elaboration

4.6. Robustness and summary of research questions

To ensure reliability, several robustness checks were performed. First, alternative proxies of audit risk were tested by isolating restatements from other indicators. Results remained consistent: AI models maintained higher predictive accuracy than logistic regression (Table 8).

Second, sector-specific analyses were conducted. In the UAE, governance factors were particularly strong predictors in non-financial sectors, while in the UK financial ratios were more important in manufacturing and services. This reinforces the context-driven nature of audit risk determinants.

Third, rolling-window tests compared pre- and post-COVID periods (2017–2020 vs. 2021–2024). Predictive accuracy improved slightly in the later period, likely due to richer disclosure and enhanced governance reforms, but the relative ranking of models remained unchanged.

Overall, the robustness checks confirm the stability and validity of the main findings. AI models consistently outperform benchmarks, and contextual differences between UAE and UK persist across specifications (Vaithilingam et al., 2024).

Model	UAE (Baseline)	UAE Restatements Only	UAE Post-2020	UK (Baseline)	UK Non-Financials	UK Post-2020
Logistic Regression	0.72	0.70	0.73	0.75	0.73	0.76
Random Forest	0.87	0.85	0.88	0.85	0.84	0.86
XGBoost	0.85	0.83	0.86	0.88	0.86	0.89
Deep Neural Net	0.84	0.82	0.85	0.86	0.84	0.87

Table 8. Robustness check results (AUC values, selected tests)

Source: Authors’ elaboration

The results show that AI models consistently outperform traditional econometric benchmarks in predicting audit risk, answering RQ1 affirmatively. The most influential drivers differ between contexts: governance factors are stronger in the UAE, while financial indicators and auditor type dominate in the UK, answering RQ2. Explainable AI tools, SHAP and LIME, improved transparency and interpretability, answering RQ3. Transferability tests revealed performance declines when models were applied across countries, answering RQ4.

Research question	Statement	Answer	Key evidence
RQ1	Do AI-based models predict audit risk more accurately than econometric approaches?	Yes	Higher accuracy, recall, and AUC across UAE and UK
RQ2	Do key audit risk drivers differ between UAE and UK?	Yes	Governance variables dominate in UAE; financial and auditor variables dominate in UK
RQ3	Do SHAP and LIME enhance interpretability and trust?	Yes	SHAP feature ranking and LIME case-level explanations clarify model outputs
RQ4	Do AI models lose accuracy when applied cross-country?	Yes	AUC declines when UAE-trained models are applied to UK firms and vice versa

Table 9. Summary of research-question answers

Source: Authors’ elaboration

5. DISCUSSION

Traditional econometric models, particularly logistic regression and probit, have long been favoured in audit research for their transparency and ease of interpretation. However, they suffer from rigid assumptions of linearity and stability, limiting their ability to capture complex and dynamic interactions among financial, governance, and market variables (Zhong et al., 2024; Arsyad et al., 2025). The findings of this study reinforce these critiques. Regression models explained only a modest share of audit risk and displayed varying predictive power across the UAE and UK. In the UAE, governance indicators such as board independence and ownership concentration emerged as the dominant predictors, while in the UK, profitability and Big 4 affiliation were more significant. This divergence supports prior claims that econometric approaches, while interpretable, often fail to provide robust or generalisable insights in heterogeneous contexts.

By contrast, artificial intelligence (AI) models demonstrated their superiority in addressing these shortcomings. Recent literature has highlighted the ability of ensemble methods such as Random Forest and XGBoost, along with deep neural networks, to model non-linear relationships and uncover hidden patterns in high-dimensional datasets (Qatawneh, 2025). The results of this study confirm these arguments. AI models consistently outperformed econometric benchmarks across both countries, achieving higher accuracy, recall, and AUC, with performance levels above 0.85. These outcomes confirm the growing consensus that AI constitutes a methodological advance in audit risk modelling (Abdelwahed et al., 2025). More importantly, the study illustrates that AI can adapt to the distinctive features of both emerging and mature audit environments.

Nevertheless, predictive strength alone is insufficient in auditing, where transparency and trust are indispensable. A recurring critique of AI is its “black-box” nature, which can hinder regulatory acceptance and professional judgment (Hassija et al., 2024; Sachan & Liu, 2024). Explainable AI (XAI) has been proposed as a solution, yet its use in auditing remains limited (Gebreyesus et al., 2024). Explainability outputs should, however, be interpreted with caution: SHAP and LIME are post-hoc approximations that can simplify complex non-linear relationships, and they do not by themselves establish causal mechanisms (Alshehadeh et al., 2025). By integrating SHAP and LIME, this study provides empirical evidence that AI models can be both powerful and interpretable. SHAP

values revealed governance variables as the key drivers of audit risk in the UAE and profitability and Big 4 affiliation in the UK. LIME further validated these insights at the firm level, demonstrating how individual cases align with broader model patterns. These findings extend prior work by showing that explainability tools can effectively reconcile methodological sophistication with professional accountability.

A further contribution lies in testing transferability across institutional settings. Existing studies acknowledge the importance of institutional context but rarely examine whether models trained in one jurisdiction can be applied elsewhere (Alharasis et al., 2024; Lisina et al., 2024). This study shows that AI models lose predictive accuracy when transferred cross-country, underscoring that audit risk determinants are context-bound, influenced by governance systems, disclosure quality, and regulatory oversight. For example, a UAE-trained Random Forest model dropped from an AUC of 0.87 to 0.78 when applied to UK firms, while the UK-trained XGBoost model declined similarly when applied in the UAE. These results highlight both the promise and the boundaries of AI in comparative audit risk analysis.

These cross-country patterns also speak to the debate on auditing standard convergence. The within-country success of AI models suggests that common principles (e.g., documentation, validation, and explainability expectations) could support more unified oversight, but the observed decline in transferability implies that institutional implementation remains pivotal. In practice, this points to a hybrid approach: shared global guardrails for AI use in auditing, combined with locally calibrated risk models and jurisdiction-specific governance and enforcement indicators.

A related limitation concerns potential data and model bias. Cross-country differences in disclosure depth, enforcement intensity, and the availability of governance data can affect the comparability of risk labels and predictors. Future work should therefore evaluate subgroup performance (e.g., by sector and firm size), test calibration and error asymmetries, and consider fairness-aware modelling strategies when AI outputs are intended for operational deployment.

Finally, the strictly quantitative design should be interpreted as modelling risk signals, not replacing the human element of audit work. Audit engagement decisions involve professional judgment, client-specific knowledge, and iterative

evidence evaluation. Accordingly, AI-based risk scoring is most defensible when used in a human-in-the-loop workflow (triage, planning, and targeted testing), with engagement partners retaining accountability and using explainability outputs as prompts for inquiry rather than as final verdicts.

Taken together, the discussion advances three points. First, AI outperforms econometric approaches in predictive accuracy, confirming its methodological value. Second, embedding SHAP and LIME demonstrates that accuracy and interpretability can co-exist, addressing the transparency concerns central to auditing. Third, institutional context remains decisive, with governance shaping risk in emerging markets and financial performance dominating in mature markets. Thus, AI-driven audit risk models should be customised to regulatory environments rather than assumed to be universally transferable.

This study carries significant implications for research, practice, policy, and managerial decision-making.

From a research perspective, the results reaffirm the limitations of econometric models and highlight the methodological contribution of AI-based approaches. By demonstrating that Random Forest, XGBoost, and deep neural networks capture complex and non-linear interactions with markedly higher accuracy, the study addresses long-standing concerns about the rigidity of conventional methods. More importantly, the integration of SHAP and LIME illustrates that advanced techniques need not sacrifice interpretability. This dual emphasis on accuracy and transparency enriches the modelling literature by showing that methodological sophistication can be harmonised with accountability, thereby extending the theoretical conversation on the role of explainable AI in management science.

For practice, the findings underline that audit risk determinants are shaped by institutional context. In the UAE, governance variables such as ownership concentration and board independence are decisive, whereas in the UK financial performance and auditor type dominate. This divergence suggests that audit firms, multinational corporations, and professional service providers should resist applying uniform frameworks and instead design models sensitive to local institutional conditions. Embedding explainable AI further strengthens professional decision-making by enabling auditors, boards, and audit committees to interrogate and validate outputs. This not only enhances confidence in the use of AI tools but also fosters more effective integration of these technologies into audit engagements.

At the policy level, the study highlights the urgency of regulatory adaptation to technological advances. The evidence that explainable AI clarifies the rationale behind risk assessments provides regulators with a practical basis to incorporate AI tools into oversight frameworks. This is particularly critical in emerging markets, where enhancing governance credibility and investor confidence remains a pressing priority. For mature markets, the adoption of transparent AI-driven models can bolster accountability and mitigate reputational risks in the wake of high-profile audit failures. More broadly, transparent AI-enabled audit risk frameworks can contribute to market resilience, improved regulatory oversight, and strengthened public trust in financial reporting, underscoring their wider societal value. Recent policy developments illustrate this direction, including the UK Financial Reporting Council's guidance on the use of AI in audit (Financial Reporting Council [FRC], 2025a), annual audit firm inspection results (FRC, 2025b), and strengthened regulatory cooperation in the UAE audit environment (Dubai Financial Services Authority, 2025).

Finally, at the managerial level, the study offers actionable insights for CFOs, audit committees, and boards of directors. The evidence that risk drivers vary across contexts underscores the need for management teams to align risk assessment models with their specific governance structures, financial profiles, and market conditions. Explainable AI outputs can be incorporated into board-level dashboards, enabling decision-makers to visualise how particular financial or governance factors affect audit risk. Such integration not only enhances internal risk monitoring but also equips managers to engage more effectively with auditors, regulators, and investors, thereby strengthening corporate accountability and strategic resilience.

6. CONCLUSIONS

This study set out to evaluate audit risk modelling by comparing traditional econometric approaches with advanced AI methods in two contrasting institutional contexts, the UAE and the UK. The central aim was to assess predictive accuracy, interpretability, and transferability of models, while examining how institutional environments condition the determinants of audit risk.

The findings demonstrate novelty in three dimensions. First, they provide clear empirical evidence that AI techniques such as Random Forest, XGBoost, and deep neural networks consistently outperform econometric benchmarks in predictive

accuracy. This validates growing calls in the literature for dynamic, data-driven approaches capable of addressing the non-linear and high-dimensional nature of audit risk. Second, by embedding SHAP and LIME into the modelling framework, the study shows how predictive power can be combined with interpretability, an aspect rarely integrated in prior audit research. This dual emphasis directly addresses concerns about the opacity of AI systems and demonstrates that accountability and methodological sophistication can co-exist. Third, the comparative design reveals that governance variables dominate in an emerging market such as the UAE, while financial and audit characteristics carry more weight in a mature market like the UK. This context-sensitive contribution advances understanding of both methodological and institutional dimensions of audit risk modelling.

Despite these contributions, several limitations are acknowledged. The reliance on secondary data may have constrained the depth and granularity of governance measures. Cross-country analysis improves generalisability, yet the focus on only two markets limits the scope of institutional variation. Additionally, although explainable AI tools enhance interpretability, they remain approximations and may oversimplify complex relationships. These limitations delineate the boundaries of the present study while highlighting opportunities for further research. In addition, post-hoc explainability tools provide approximations rather than full representations of model reasoning, and cross-country differences in enforcement and disclosure can introduce bias in both labels and predictors; these factors should temper strong claims of generalisability.

Future studies should extend this comparative framework to a broader set of countries across diverse regulatory environments, particularly within Asia, Africa, and Latin America, to further test the transferability of AI-based audit risk models. Mixed-method approaches that combine quantitative modelling with qualitative interviews of auditors, regulators, and corporate boards could enrich insights into how explainable AI is perceived and applied in practice. Longitudinal designs would also help capture the dynamic effects of regulatory reforms, technological adoption, and evolving corporate governance on audit risk determinants.

In light of the findings, several targeted recommendations can be advanced for different stakeholders.

For researchers, the priority is to broaden methodological frontiers. Future studies should not only compare AI with econometric models but also explore hybrid designs that integrate machine learning with advanced text analytics, such as natural language processing of audit disclosures and annual reports. This would allow researchers to capture qualitative dimensions of audit risk that are often overlooked. Expanding to cross-regional datasets and incorporating longitudinal analysis would further enhance robustness and generalisability. A particularly promising direction is Natural Language Processing (NLP) of narrative disclosures—especially the Management Discussion and Analysis (MD&A) sections—to extract tone, readability, forward-looking risk signals, and governance narratives, and then test whether these text-derived features improve model transferability across jurisdictions.

For practitioners, audit firms should move beyond static, uniform risk models and adopt AI frameworks calibrated to specific institutional and regulatory contexts. Practical steps include developing tailored AI modules for industry sectors, piloting explainable AI in client engagements, and training audit teams in interpreting SHAP and LIME outputs to support professional judgment. These actions will ensure that AI tools complement, rather than replace, auditor expertise.

For regulators, the key task is to provide structured pathways for safe experimentation with AI in audit oversight. Establishing regulatory sandboxes, issuing interpretive guidance on acceptable uses of explainable AI, and creating auditability standards for algorithms would reduce uncertainty and encourage responsible innovation. This proactive stance will also help align technological adoption with public trust requirements.

For corporate managers, especially CFOs and boards, AI-driven audit risk dashboards should be integrated into governance and oversight systems. These dashboards can provide real-time visualisations of how financial, governance, and market indicators affect risk exposure, enabling leaders to strengthen oversight, anticipate vulnerabilities, and communicate risks more effectively to stakeholders.

In sum, this study demonstrates that AI, when combined with explainability, offers a powerful and transparent alternative to traditional econometric models. By situating the analysis within contrasting institutional contexts, it not only advances methodological innovation but also provides practical pathways for enhancing audit quality, regulatory oversight, and corporate governance across diverse markets.

7. REFERENCES

- Abdelwahed, A. S., Abu-Musa, A. A. E. S., Badawy, H. A. E. S., & Moubarak, H. (2025). Investigating the impact of adopting big data and data analytics on enhancing audit quality. *Journal of Financial Reporting and Accounting*, 23(2), 472–495. <https://doi.org/10.1108/JFRA-12-2023-0724>
- Abu Huson, Y., Sierra García, L., García Benau, M. A., & Mohammad Aljawarneh, N. (2025). Cloud-based artificial intelligence and audit report: The mediating role of the auditor. *VINE Journal of Information and Knowledge Management Systems*, 55(6), 1553–1574. <https://doi.org/10.1108/VJIKMS-03-2024-0089>
- Abubakr, A. A. M., Khan, F., Alomari, K. M., Sahal, M. S. G., Yousif, N. A. I., & Yousif, H. K. (2025). The role of the internal auditor, stakeholders, and external auditor in discovering and reducing creative accounting practices in UAE companies. *Security Journal*, 38(1), 31. <https://doi.org/10.1057/s41284-025-00478-0>
- Ahmad, A. K., Nahar, H. M., & Manajreh, M. M. N. (2023). Effect of social media on shaping the agenda of the communicator in the Jordanian TV channels. *Middle East Journal of Communication Studies*, 3(2), 1–40. <https://doi.org/10.71220/2585-003-002-003>
- Algrady, S. M., Huang, R., & Al-Matari, E. M. (2025). How do audit committee characteristics affect the quality of financial information? Evidence from Saudi Arabia and United Arab Emirates companies. *SAGE Open*, 15(2). <https://doi.org/10.1177/21582440251317803>
- Alharasis, E. E., Prokofieva, M., Clark, C., Haddad, H., & Alramahi, N. (2024). The development of international accounting and auditing standards for fair value accounting in the Arab Middle East, Jordan: A systematic review. *Cogent Business & Management*, 11(1), 2391564. <https://doi.org/10.1080/23311975.2024.2391564>
- Al-Muntasir, M. (2022). The phenomenon of information flow from traditional and new media about the Corona pandemic from the perspective of newly graduated media professionals in Yemen. *Middle East Journal of Communication Studies*, 2(2). <https://mejcs.meu.edu.jo/?p=1781> Accessed 26 June 2025.

Alsmadi, A. A., & Alrawashdeh, N. (2025). The role and implications of finance revaluation: A comprehensive literature review. *Al-Zaytoonah Journal of Business*, *1*(1), 1–12. <https://doi.org/10.15849/zjzb.v1i01.31>

Alshehadeh, A. R., Abu Nahleh, I. T., & Al-Zyoud, I. A. (2025). The impact of financial and non-financial information on investment decision-making in the Jordanian business environment. *Al-Zaytoonah Journal of Business*, *1*(1), 1–8. <https://doi.org/10.15849/zjzb.v1i01.39>

Al-Omush, A., Almasarwah, A., & Al-Wreikat, A. (2025). Artificial intelligence in financial auditing: Redefining accuracy and transparency in assurance services. *EDPACS*, *70*(6), 1–20. <https://doi.org/10.1080/07366981.2025.2459490>

Arsyad, I., Kharisma, D. B., & Wiwoho, J. (2025). Artificial intelligence and Islamic finance industry: Problems and oversight. *International Journal of Law and Management*, *66*(5), 420–433. <https://doi.org/10.1108/IJLMA-07-2024-0236>

Bader, A., Qtaish, A., Odeh, K., & Sa'd, H. (2025). Artificial intelligence and big data in accounting: The case of commercial banks in Jordan. *Al-Zaytoonah Journal of Business*, *1*(3), 1–18. <https://doi.org/10.15849/zjzb.v1i03.49>

Bertozzi, O., Chamorro, H. R., Gomez-Diaz, E. O., Chong, M. S., & Ahmed, S. (2024). Application of data-driven methods in power systems analysis and control. *IET Energy Systems Integration*, *6*(3), 197–212. <https://doi.org/10.1049/esi2.12122>

Chen, J. Z., Elemen, A., Hope, O.-K., & Yoon, A. S. (2024). Audit-firm profitability: Determinants and implications for audit outcomes. *European Accounting Review*, *33*(4), 1369–1396. <https://doi.org/10.1080/09638180.2023.2169735>

Dhou, K., & Orudzheva, L. (2025). Data integrity and AI ethics. In *Institutional guide to using AI for research* (pp. 185–204). Springer. https://doi.org/10.1007/978-3-031-94809-1_9

Dubai Financial Services Authority. (2025). The SCA and DFSA strengthen regulatory cooperation through a memorandum of understanding for the oversight of auditors. <https://www.dfsa.ae/news/sca-and-dfsa-strengthen-regulatory-cooperation-memorandum-understanding-oversight-auditors> Accessed 27 October 2025

Financial Reporting Council. (2025a). AI in audit: Illustrative example and documentation guidance. <https://www.frc.org.uk/library/standards-codes-policy/audit-assurance-and-ethics/guidance/ai-in-audit/> Accessed 26 June 2025.

Financial Reporting Council. (2025b). FRC publishes annual audit firm inspection results. <https://www.frc.org.uk/news-and-events/news/2025/07/frc-publishes-an-nual-audit-firm-inspection-results/> Accessed 15 July 2025

Gafsi, N. (2025). Machine learning approaches to credit risk: Comparative evidence from participation and conventional banks in the UK. *Journal of Risk and Financial Management*, 18(7), 345. <https://doi.org/10.3390/jrfm18070345>

Gebreyesus, Y., Dalton, D., De Chiara, D., Chinnici, M., & Chinnici, A. (2024). AI for automating data center operations: Model explainability in the data centre context using Shapley additive explanations (SHAP). *Electronics*, 13(9), 1628. <https://doi.org/10.3390/electronics13091628>

Haapamäki, E. E., & Mäki, J. (2024). An analysis of comment letters on a new, stand-alone standard for audits of less complex entities' financial statements. *Journal of Accounting Literature*, 46(1), 51–81. <https://doi.org/10.1108/JAL-12-2022-0131>

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation*, 16(1), 45–74. <https://doi.org/10.1007/s12559-023-10179-8>

Hemachandran, K., Verma, P., Pareek, P., Arora, N., Rajesh Kumar, K. V., Ahanger, T. A., Pise, A. A., & Ratna, R. (2022). Artificial intelligence: A universal virtual tool to augment tutoring in higher education. *Computational Intelligence and Neuroscience*, 2022, 1410448. <https://doi.org/10.1155/2022/1410448>

Liew, A., Boxall, P., & Setiawan, D. (2022). The transformation to data analytics in Big-Four financial audit: What, why and how? *Pacific Accounting Review*, 34(4), 569–584. <https://doi.org/10.1108/PAR-06-2021-0105>

Lisina, N., Ushakova, A., & Ivanova, S. (2024). Green belt legislation regulation: Comparative legal research. *Laws*, 13(5), 58. <https://doi.org/10.3390/laws13050058>

Mattar, D., Khoury, R. E., & Chaanine, M. (2024). Factors affecting auditor change decisions: The case of United Kingdom. *SAGE Open*, 14(3). <https://doi.org/10.1177/21582440241259844>

Mohamed, S. D., Ismail, M. T., & Ali, M. K. B. M. (2025). Improving detectability of the indicator saturation approach through winsorization: An empirical study in the cryptocurrency market. *Statistics in Transition New Series*, 26(1), 155–181. <https://doi.org/10.59139/stattrans-2025-009>

Morshed, A. (2026). Comparative analysis of accounting standards in the Islamic banking industry: A focus on financial leasing. *Journal of Islamic Accounting and Business Research*, 17(1), 59–73. <https://doi.org/10.1108/JIABR-12-2022-0349>

Morshed, A. (2024). Evaluating the effects of IFRS 9 on Jordanian banks' credit and financial metrics. *Banks and Bank Systems*, 19(4), 70–83. [https://doi.org/10.21511/bbs.19\(4\).2024.06](https://doi.org/10.21511/bbs.19(4).2024.06)

Morshed, A. (2025). Navigating tradition and modernity: Digital accounting and financial integration in family-owned enterprises in the Arab Gulf. *Sustainable Futures*, 9, 100680. <https://doi.org/10.1016/j.sftr.2025.100680>

Oreqat, A. (2021). The degree of satisfaction of Facebook users about its features, usage motives and achieved gratifications: An applied study on students of the Faculty of Mass Communication at the Middle East University to attract attention. *Middle East Journal of Communication Studies*, 1(1), 1. <https://digitalcommons.aaru.edu.jo/mejcs/vol1/iss1/1> Accessed 26 June 2025.

Othman, M. (2025). Evolving financial practices in family enterprises: The impact of generational dynamics on digital transformation in Jordan. *Investment Management & Financial Innovations*, 22(2), 141–154. [https://doi.org/10.21511/imfi.22\(2\).2025.12](https://doi.org/10.21511/imfi.22(2).2025.12)

Perry, Y. K. Z., Adrian, C., & Truong, C. (2025). Politically connected audit committee and audit risk: Evidence from a quasi-experiment. *Accounting & Finance*, 65(2), 1428–1467. <https://doi.org/10.1111/acfi.13373>

Pu, Y., Zhou, X., Zhang, D., Guan, Y., Xia, Y., Tu, W., Lu, Y., Zhang, W., Fu, C.-C., & Fang, Q. (2022). Re-defining high risk COPD with parameter response mapping based on machine learning models. *International Journal of Chronic Obstructive Pulmonary Disease*, 17, 2471–2483. <https://doi.org/10.2147/COPD.S369904>

Qatawneh, A. M. (2025). The role of artificial intelligence in auditing and fraud detection in accounting information systems: Moderating role of natural language processing. *International Journal of Organizational Analysis*, 33(6), 1391–1409. <https://doi.org/10.1108/IJOA-03-2024-4389>

Ramadan, A., & Morshed, A. (2024). Impact of international accounting standards on Hungary's financial transparency. *Investment Management and Financial Innovations*, 21(4), 11–24. [https://doi.org/10.21511/imfi.21\(4\).2024.02](https://doi.org/10.21511/imfi.21(4).2024.02)

Rane, N., Choudhary, S., & Rane, J. (2024). Artificial intelligence for enhancing resilience. *Journal of Applied Artificial Intelligence*, 5(2), 1–33. <https://doi.org/10.48185/jaai.v5i2.1053>

Riskiyadi, M. (2024). Detecting future financial statement fraud using a machine learning model in Indonesia: A comparative study. *Asian Review of Accounting*, 32(3), 394–422. <https://doi.org/10.1108/ARA-02-2023-0062>

Sachan, S., & Liu, X. (2024). Blockchain-based auditing of legal decisions supported by explainable AI and generative AI tools. *Engineering Applications of Artificial Intelligence*, 129, 107666. <https://doi.org/10.1016/j.engappai.2023.107666>

Shaban, O. S., & Barakat, A. I. (2023). Evaluation of internal audit standards as a foundation for carrying out and promoting a wide variety of value-added tasks—Evidence from emerging market. *Journal of Risk and Financial Management*, 16(3), 185. <https://doi.org/10.3390/jrfm16030185>

Shaban, O. S., & Omoush, A. (2025). AI-driven financial transparency and corporate governance: Enhancing accounting practices with evidence from Jordan. *Sustainability*, 17(9), 3818. <https://doi.org/10.3390/su17093818>

Shakir, M. A., Abass, H. K., Jelwy, O. F., Al-Bayati, H. N. A., Salman, S. M., Mikhav, V., & Bodnar, N. (2024). Developing interpretable models for complex decision-making. In *2024 36th Conference of Open Innovations Association*

- (FRUCT) (pp. 66–75). IEEE. <https://doi.org/10.23919/FRUCT64283.2024.10749922>
- Sithakoul, S., Meftah, S., & Feutry, C. (2024). Beexai: Benchmark to evaluate explainable AI. In *World Conference on Explainable Artificial Intelligence* (pp. 445–468). Springer. https://doi.org/10.1007/978-3-031-63787-2_23
- Srairi, S. (2025). ESG performance in GCC banks: The influence of ownership structure, risk attitude and board characteristics in Islamic vs conventional contexts. *Sustainability Accounting, Management and Policy Journal*, 17(4), 1092–1138. <https://doi.org/10.1108/SAMPJ-11-2024-1190>
- Sukma, N., & Namahoot, C. S. (2025). Enhancing trading strategies: A multi-indicator analysis for profitable algorithmic trading. *Computational Economics*, 65(6), 3807–3840. <https://doi.org/10.1007/s10614-024-10729-4>
- Taqa, S. B. A. (2025). The mediating role of remote communication on the relationship between electronic human resource management practices and organizational performance in Iraqi commercial banks. *Middle East Journal of Communication Studies*, 5(1), 2. <https://doi.org/10.71220/2585-005-001-001>
- Thapa, C., Chamikara, M. A. P., & Camtepe, S. A. (2021). Advancements of federated learning towards privacy preservation: From federated learning to split learning. In *Federated learning systems: Towards next-generation AI* (pp. 79–109). Springer. https://doi.org/10.1007/978-3-030-70604-3_4
- Tumewang, Y. K., Ntim, C. G., & Haque, F. (2025). Task Force on Climate-Related Financial Disclosures: A systematic literature review and future research agenda. *Business Strategy and the Environment*, 34(8), 10033–10058. <https://doi.org/10.1002/bse.70112>
- United Arab Emirates. (2023). *Federal Decree-Law No. (41) of 2023 on regulating the accounting and auditing profession*. UAE Legislation. <https://uaelegislation.gov.ae/en/legislations/2183/download> Access 16 March 2026
- Vaithilingam, S., Ong, C. S., Moisescu, O. I., & Nair, M. S. (2024). Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research. *Journal of Business Research*, 173, 114465. <https://doi.org/10.1016/j.jbusres.2023.114465>

- Wang, W., & Guedes, M. J. (2025). Firm failure prediction for small and medium-sized enterprises and new ventures. *Review of Managerial Science*, 19(7), 1949–1982. <https://doi.org/10.1007/s11846-024-00742-4>
- Wu, J., Xue, Y., Zhang, Q., & Liu, Y. (2024). Digital economy, financial development, and corporate green technology innovation. *Finance Research Letters*, 66, 105552. <https://doi.org/10.1016/j.frl.2024.105552>
- Zheng, X., Li, J., Lu, M., & Wang, F.-Y. (2024). New paradigm for economic and financial research with generative AI: Impact and perspective. *IEEE Transactions on Computational Social Systems*, 11(3), 3457–3467. <https://doi.org/10.1109/TCSS.2023.3334306>
- Zhong, H., Yang, D., Shi, S., Wei, L., & Wang, Y. (2024). From data to insights: The application and challenges of knowledge graphs in intelligent audit. *Journal of Cloud Computing*, 13, 114. <https://doi.org/10.1186/s13677-024-00674-0>