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Article

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Borsa İstanbul Review

Provided in Cooperation with:

Borsa İstanbul Anonim Şirketi, İstanbul

Suggested Citation: Ali, Hassnian; Aysan, Ahmet Faruk (2025) : Decoding digital signals: AI sentiment and financial performance at Islamic banks, Borsa İstanbul Review, ISSN 2214-8469, Elsevier, Amsterdam, Vol. 25, Iss. 5, pp. 953-971,
<https://doi.org/10.1016/j.bir.2025.05.011>

This Version is available at:

<https://hdl.handle.net/10419/340617>

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Decoding digital signals: AI sentiment and financial performance at Islamic banks

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ARTICLE INFO

JEL classification:

C55
G21
G32
O16

Keywords:

Artificial intelligence
Islamic banking
Machine learning

ABSTRACT

This study provides empirical evidence on the role of artificial intelligence (AI) and machine learning (ML) sentiment in influencing financial performance by Islamic banks. Using advanced textual analysis methods, including long short-term memory (LSTM) networks, AI and ML sentiment is derived from annual reports. The study employs fixed-effects regression using the return on equity (ROE) as the primary measure and robustness checks using random forest models and spline regressions to examine their impact on ROE and the return on assets (ROA). It also investigates the mediating role of the development of information communication technologies (ICT) and the moderating effect of growth in the gross domestic product (GDP). Our findings reveal that positive sentiment about AI and ML significantly enhances profitability, and combined sentiment has the strongest predictive power. The mediating role of ICT development highlights the importance of digital infrastructure, and GDP growth emphasizes the contextual dependence of AI-driven innovation.

1. Introduction

Integrating artificial intelligence (AI) and machine learning (ML) technologies into the financial sector has accelerated structural changes, redefined operational frameworks, and promoted innovation. These technologies enable financial institutions to improve decision-making, automate processes, and craft data-informed strategies, thereby maintaining their competitiveness in a rapidly digitizing global economy (Choudhary & Arora, 2024). In this context, sentiment analysis—an application of AI and ML—facilitates the extraction of actionable insights from textual data, including annual reports and customer feedback, which increasingly shape institutional outcomes (Jiang et al., 2023; Mohanty & Cherukuri, 2023). Despite the increase in research on sentiment analysis in conventional banking, its use and implications in Islamic banking are largely underexplored. This study fills this gap by presenting the first empirical evidence on how AI and ML sentiment extracted from internal disclosures influences the financial performance of Islamic banks.

Islamic banks operate under sharia principles, prohibiting interest-based transactions and speculative activities while promoting risk sharing and ethical investment. These constraints necessitate high efficiency and innovation to ensure the banks' long-term viability in a

shifting financial landscape (M. Rahman, Ming, Baigh, & Sarker, 2023). In this regard, AI and ML technologies have demonstrated strong potential to enhance risk modeling, operational efficiency, and customer experience in both conventional (Baffour Gyau, Appiah, Gyamfi, Achie, & Naeem, 2024) and Islamic banking environments (Shiyyab, Alzoubi, Obidat, & Alshurafat, 2023; Thornton & Di Tommaso, 2021). Sentiment analysis, in particular, equips Islamic banks with the strategic capability to align internal communication with stakeholder expectations, support product innovation, and enhance customer trust while remaining compliant with sharia. Nonetheless, effectively implementing these technologies requires overcoming barriers such as high deployment costs, regulatory challenges, and insufficient ICT infrastructure (Hu & Wu, 2023).

Although the utility of AI-based sentiment analysis in conventional finance has been established (Hassan, 2023; Moro-Visconti, 2024), its role in Islamic banking is insufficiently examined. Existing research has also overlooked the influence of AI on financial outcomes and the possibly time-dependent nature of these effects. This study empirically evaluates the effect of AI and ML sentiment scores on financial performance, specifically the return on equity (ROE) and the return on assets (ROA), at Islamic banks. It also examines the moderating role of economic growth and the mediating role of ICT development, expanding

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<https://doi.org/10.1016/j.bir.2025.05.011>

Received 11 February 2025; Received in revised form 17 May 2025; Accepted 17 May 2025

Available online 21 May 2025

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the conceptual scope of studies on AI performance.

This paper is motivated by recent studies that investigate the intersection of AI, sustainable finance, and Islamic financial systems. Abakah, Tiwari, Ghosh, and Doğan (2023) examine the effects of financial technology (fintech), Bitcoin, and AI stocks on green and Islamic financial assets using quantile-based methods, revealing significant market-specific sensitivity. Their findings support the view that AI-related innovations may have different financial outcomes in Islamic markets than elsewhere. Likewise, using wavelet-based techniques, Tiwari, Abakah, Doğan, and Ghosh (2023) assess the relationship between sustainable debt and gas markets, showing that the relationship varies over time. Following this evidence, we use lagged models and nonlinear techniques to explain how sentiment evolves and affects performance. Moreover, Kumar, Rahman, Rajverma, and Misra (2024) and Alam, Rabbani, Tausif, and Abey (2021) emphasize the need for integrated approaches when emerging technologies are studied in regulated financial systems. Collectively, these studies confirm that examining AI adoption in Islamic banking using advanced sentiment modeling frameworks is important and timely.

This study employs a rigorous empirical framework that combines econometric and ML approaches to obtain robust and replicable insights. The main independent variables are three sentiment indicators: AI sentiment score, ML sentiment score, and Combined sentiment score. They are derived through advanced natural language processing, using long short-term memory (LSTM) networks. The control variables to account for structural and macroeconomic variation include bank size, the nonperforming loan ratio, growth in the gross domestic product (GDP), regulatory quality, and internet penetration. Spline regression and random forest algorithms help in the identification of nonlinear patterns and variable interactions, and lagged models reveal temporal dependence.

Our findings confirm that AI and ML sentiment significantly influence Islamic banks' profitability, and the Combined sentiment score consistently has the highest predictive strength. ICT development acts as an enabling condition, translating sentiment into improved performance, and economic growth moderates the strength of these effects. The results of robustness checks confirm these findings, identifying additional conditional and nonlinear effects. Lagged analyses reveal that performance gains emerge progressively and might taper off as the technologies mature.

This study makes several contributions to the literature. It presents the first empirical analysis of sentiment-based AI and ML measures in Islamic banking, filling a critical research gap. The research advances methodological practices in financial technology studies by combining traditional statistical tools with ML models. By identifying the conditions under which sentiment-based AI strategies are most effective, the results also have practical implications for banks, regulators, and policymakers in Islamic finance. A key determinant of long-term success is strategic alignment between AI deployment, regulatory flexibility, and ICT readiness. Thus, this paper lays a foundation for future studies on the impact of technological sentiment on organizational performance at faith-based financial institutions.

The paper is structured as follows. Section 2 presents the theoretical framework and hypothesis development, as well as a literature review. Section 3 outlines the methodology, model, data sources, and variables. The results and robustness checks are presented in Section 4, followed by. The paper concludes in Section 5 with a discussion of implications, limitations, and directions for future research.

2. Theoretical framework, literature review, and development of hypotheses

2.1. Theoretical framework

In the evolving context of global banking, analyzing how AI technology innovations affect the financial performance of Islamic banks—a

distinct yet integral component of the global banking system—requires multiple theoretical perspectives. They include examining AI capabilities as strategic resources (resource-based view), understanding the spread of these capabilities across diverse markets (diffusion of innovation theory), and recognizing how regulatory and cultural environments shape their implementation (institutional theory). This study offers a holistic framework for comprehending AI-driven change in Islamic finance by combining these perspectives.

According to the resource-based view (RBV), organizations attain superior performance by using resources that are valuable, rare, and difficult to imitate (Barney, 1991). In Islamic banking, AI technology innovation can function as a strategic resource that optimizes internal processes and upholds the ethical and sharia-compliant principles that are central to Islamic finance. When Islamic banks leverage advanced AI tools—such as ML for credit evaluation or automated financial advisory services guided by Islamic regulations—they can obtain a competitive advantage that is difficult for other institutions to replicate. Adopting these AI capabilities can enhance operational efficiency, reinforce risk management frameworks, and provide personalized, sharia-compliant client services, thereby strengthening financial performance indicators, such as ROA and ROE. However, RBV may face limitations if these AI-based resources fail to align with a bank's strategic objectives or if competing Islamic banks adopt similar solutions, eroding any initial performance advantages (Md. M. Rahman, 2023).

The **diffusion of innovation (DoI) theory** also explains how AI technologies are adopted and disseminated in the Islamic banking sector, as well as their effects on financial outcomes (Rogers, Singhal, & Quinlan, 2019). According to DoI, an innovation typically begins with a small group of early adopters before gradually gaining acceptance in the broader market. When applied to Islamic banking, this theory can illuminate differences in AI adoption rates across regions, clarify the timeline of AI implementation, and demonstrate how these patterns relate to improvements in bank performance. Factors such as technological preparedness, sharia governance structures, and client demand significantly influence how quickly AI solutions spread in Islamic financial institutions, thus informing how AI enhancements are manifested in metrics such as profitability and efficiency (Shiyyab et al., 2023). But evidence about DoI might be conflictual if some Islamic banks encounter barriers—due to regulatory constraints, concerns regarding sharia compliance, and cultural attitudes—to the successful uptake of AI technologies.

Moreover, **institutional theory** explores how regulatory environments, cultural norms, and broader institutional factors affect the adoption of AI in Islamic finance (Mayntz, 1996). Islamic banks are subject to various institutional pressures, including global regulatory frameworks, local sharia supervisory boards, and social expectations—all of which can either foster or impede AI initiatives. For instance, an Islamic bank may pursue AI solutions only after rigorous vetting to ensure compliance with Islamic law and ethical guidelines, thereby solidifying stakeholder trust and potentially improving financial performance. However, conflicting outcomes might be produced if stringent regulations, diverse cultural factors, and contrasting views of sharia compliance slow the integration of AI solutions, limiting their impact on key performance indicators. Variability in international regulatory standards can also produce uneven opportunities for AI adoption, which may reduce anticipated benefits.

By combining these theoretical lenses, this study offers a comprehensive appraisal of AI technology innovation in Islamic banking. RBV emphasizes that AI is a strategic resource for competitive advantage, DoI focuses on the stages and patterns in AI adoption, and institutional theory highlights the significance of regulatory and social contexts. Together, these frameworks clarify how AI technologies can improve financial outcomes at Islamic banks, while also acknowledging the potential contradictions when strategic, institutional, or market-related barriers to AI adoption emerge.

2.2. Literature review

In the contemporary banking literature, **ROE** is frequently a core indicator of profitability (Alalmaee, 2024; Kumar et al., 2024; Rehan, Khan, Fu, Sa'ad, & Irshad, 2024). Various studies have highlighted important determinants of banks' financial outcomes, including nonperforming loans (NPLs; Takahashi & Vasconcelos, 2024), regulatory capital (de Bandt, Camara, Maitre, & Pessarossi, 2018), macroeconomic growth (Alam et al., 2021), government regulation (Bătae, Dragomir, & Feleagă, 2021), and ICT development (Al-Busaidi & Al-Muharrami, 2021). At Islamic banks in particular, managing these factors can be more complex because of the sharia compliance requirement, which influences the operational structure and overall profitability (Irfan, Kadry, Sharif, & Khan, 2023). At the same time, numerous scholars regard NPLs as a decisive variable in explaining banks' profitability: Takahashi and Vasconcelos (2024) provide evidence that high NPL ratios negatively affect ROE by constraining revenue-generating capacity and amplifying loan-loss provisions, a pattern reinforced by Duong, Tran, Nguyen, and Pham (2023). Regulatory capital also has a significant relationship with performance. Tran, Lin, and Nguyen (2016) observe that banks with a stronger capital position can benefit from an enhancement in market confidence, whereas profitability at those with a weaker position erodes as they work to meet capital thresholds. This effect might be accentuated at Islamic banks, where the capital structure must align with both prudential regulation and Islamic principles (Al-Jarrah, Al Badarin, & Almohammad, 2024).

The literature also indicates that economic growth fosters bank profitability (Ledhem & Mekidiche, 2020), whereas regulatory interventions impose either benefits or costs, depending on how governance frameworks interact with market conditions (Nasreen, Gulzar, Afzal, & Farooq, 2024). Similarly, ICT development can produce different outcomes in terms of bank returns: Aguegboh, Agu, and Nnetu-Okolieuwa (2023) find that advanced ICT use in sub-Saharan African banks reduced ROA but boosted other key metrics, which suggests that digital technologies might have complex net impacts on bank profitability. In addition, adoption of AI is increasingly raising operating efficiency and enhancing customer-related services. Studies such as Shiyyab et al. (2023) on Jordanian banks and Königstorfer and Thalmann (2020) on AI adoption in lending and payment security show that AI-driven methods raise core performance variables, including measures akin to ROE, by cutting operating costs and minimizing fraud.

Some papers likewise emphasize that ML solutions and data-driven analytics can diminish manual tasks, improve compliance, and offer refined credit risk assessments (Madhura, Panakaje, Kambali, & Riha Parvin, 2024; Ris, Stankovic, & Avramovic, 2020). AI-powered virtual assistants can reallocate human resources to more specialized tasks. Moreover, fintech innovations that combine Internet of Things (IoT), big data, and AI can bolster profit margins (Chhaidar, Abdelhedi, & Abdelkafi, 2023). Equally relevant is the notion that AI can be harnessed for Islamic financial contexts to ensure sharia compliance, encourage transparency, and foster stakeholder confidence (Ridho Kismawadi, Irfan, & Shah, 2023). Rabbani, Sarea, Khan, and Abdullah (2022) emphasize that ethical use of AI and regulation technology (RegTech) enhances trust in Islamic banking, potentially supporting profitability. They propose that AI chatbots specifically tailored to sharia standards deliver financial guidance and promptly respond to customer inquiries, increasing customer satisfaction and improving efficiency.

Baffour Gyau et al. (2024) explore the impact of AI innovation on banks' financial performance across 20 countries using Feasible Generalized Least Squares (FGLS) and Generalized Method of Moments (GMM) techniques, emphasizing the positive effects of AI on ROA and the mediating role of ICT development. It highlights the interaction between AI innovation and economic growth, the negative influence of NPLs, and diminishing returns from prolonged AI adoption. In contrast, our study uniquely focuses on Islamic banking, offering the first empirical evidence on AI innovation in this sharia-compliant context.

We employ sentiment analysis (AI, ML, and Combined sentiment scores) as key variables and combine traditional econometric models with ML methods such as random forest to assess both ROA and ROE. Additionally, our paper examines the lagged effects of sentiment scores and addresses the unique regulatory and operating dynamics of Islamic banks, providing a broader and clearer understanding of AI's transformative role in financial performance.

Sentiment analysis has become more important for capturing market perceptions and managerial attitudes that could shape financial outcomes. Celler (2024) focuses on the sentiment of central bank communications in Central and Eastern Europe and finds that variations in language complexity and tone reflect broader economic developments. In the banking sector, Plubin, Bunyatissai, Plubin, and JIAMWATTANAPONG (2024) examine customer reviews, finding that robust optimization techniques combined with Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can offer better insights into client satisfaction, especially regarding imbalanced sentiment datasets. Mohanty and Cherukuri (2023) highlight the role of sentiment in determining the market mood in banking feedback, whereas Sumathi and Sheela (2017) illustrate a hybrid approach, leveraging naïve Bayes and Support Vector Machine (SVM) to parse customer opinions, thereby helping banks to refine their services. Studies such as de Jesus and Besarria (2023) show that adding textual sentiment on managerial communications can sharpen predictions of insolvency risk, which in turn has direct implications for ROE.

In Islamic finance in particular, sentiment analysis can offer substantial benefits by gauging stakeholder trust—an essential pillar of sharia-oriented services. Iqbal, Sohail, and Malik (2023) introduce sentiment variables to predict performance, demonstrating a robust correlation between more optimistic managerial language and higher Islamic bank profitability. Razouk, Melliani, Adnani, and Mehdi Falloul (2023) show that investigating social media sentiment in Islamic finance concepts, such as “interest-free” and “risk mitigation,” yields insights into the perception of broader audiences about sharia-compliant offerings. This aligns with studies that illustrate that advanced sentiment algorithms enable Islamic banks to address consumer concerns in almost real time and solidify reputations for compliance and ethics (Alghadi et al., 2024).

Despite this emerging literature, few papers present cross-country evidence on how sentiment-based measures of AI and ML might interact with conventional drivers of ROE at Islamic banks. Many existing studies focus on single-country scenarios or omit sentiment variables. Moreover, the potential roles of internet penetration, government regulation (captured by regulatory quality), and bank-specific metrics, such as asset size or the NPL ratio, as moderators or control variables have not been comprehensively investigated. Taking into account earlier observations that combining AI, ML, and domain-specific textual analytics can clarify reputational risks and growth prospects (Celler, 2024; Permatasari & Fernandes, 2024), this study fills this empirical gap by introducing three distinct sentiment indicators—AI sentiment score, ML Sentiment Score, and a Combined sentiment score—and examining their implications for ROE across multiple Islamic banks. The approach thus combines established influences, such as NPL ratios, macroeconomic growth, bank size, and regulatory quality, with newly introduced sentiment-based indicators. By doing so, we provide a more complete understanding of how AI innovations and stakeholder perceptions translate into improved financial performance, yielding useful insights for managers, regulators, and stakeholders involved in Islamic banking.

2.3. Research hypotheses

Because of ongoing digital transformation in the banking sector, AI-based innovations are increasingly viewed as instruments capable of improving financial outcomes through optimized processes, data-driven decision-making, and targeted customer services. Nevertheless, it

remains unclear how varying degrees of **AI sentiment**, measured through textual analysis and ML-derived variables, can shape bank performance—particularly in a cross-country Islamic banking context. According to prior studies, AI initiatives can increase efficiency, reduce operating costs, and mitigate credit or compliance risks, thereby raising key profitability metrics, such as ROE (Polak, Nelischer, Guo, & Robertson, 2020). Consequently, higher positive sentiment regarding AI is expected to signal managerial optimism, strategic clarity, and market confidence, which, in turn, are likely to boost ROE.

Hypothesis 1. A positive AI sentiment score enhances banks' ROE.

Economic expansion has likewise been shown to foster an environment favorable to advanced technologies by providing wider resource availability, stronger market demand, and collaboration prospects (Chhaidar et al., 2023). In contexts of a growing GDP, Islamic banks with robust AI or ML sentiment stand to benefit from higher customer engagement, greater liquidity, and synergistic partnerships with technology innovators. As financial institutions channel their augmented revenue into AI-driven upgrades—in credit assessment, predictive analytics, and personalized banking services—the relationship between AI sentiment and ROE is expected to strengthen in periods with higher economic growth.

Hypothesis 2. GDP growth moderates the positive impact of AI sentiment on ROE, such that this effect intensifies when GDP growth is higher.

Meanwhile, the role of **ICT development** reveals another key component in amplification of the effect of AI sentiment. Empirical findings show that sustained investment in ICT infrastructure—from data storage to high-speed connectivity—is necessary for seamless AI integration (M. Rahman et al., 2023). When AI sentiment is high, banks are motivated to enhance their technological capacity, which facilitates higher operating efficiency, more effective risk management, and higher-value customer experiences. From this perspective, ICT development strengthens the link between positive AI sentiment and financial outcomes, which ultimately results in higher ROE.

Hypothesis 3. ICT development mediates the relationship between AI sentiment and ROE, indicating that stronger ICT capacity enables AI-driven gains in profitability.

3. Method, model, data, and variables

3.1. Methodology

This study builds on three key theoretical pillars—technological innovation theory, organizational signaling theory, and the RBV—to empirically examine whether sentiment about AI and ML influences the financial performance of Islamic banks. Technological innovation theory posits that the adoption of cutting-edge technologies, such as AI and ML, is essential for boosting organizational efficiency and maintaining a competitive advantage, particularly when aligned with conducive regulatory and institutional frameworks (Shiyyab et al., 2023). Organizational signaling theory holds that formal disclosures, such as annual reports, serve as strategic tools through which management communicates future intentions, institutional priorities, and digital readiness to stakeholders, regulators, and investors (de Jesus & Besarria, 2023; Iqbal et al., 2023). These disclosures often contain embedded sentiment that reflects internal confidence or caution regarding strategic directions. RBV complements these views by positioning intangible assets—such as technological capabilities, ICT infrastructure, and managerial expertise—as unique strategic resources that enhance firm performance (Edwina & Mauritsius, 2024; Permatasari & Fernandes, 2024).

In employing these theories, this study follows several prior works that have used sentiment analysis of annual reports to forecast financial performance. For instance, Hasan, Sufi, Elmarzouky, and Hussainey

(2024) and Qin and Cui (2024) employ text mining of the narrative disclosure tone and identified significant correlations between sentiment and firm-level outcomes. Similarly, Zhao, Song, Huang, and Kim (2025) develop a sentiment-based early warning system using annual report data, confirming the predictive strength of internal communications. Studies by Wang, Zheng, and Zhang (2024), Jena, Das, and Kar (2024), and Hájek (2018) confirm that sentiments extracted from annual reports can meaningfully predict innovation investment, ROA, and financial distress, respectively. Moreover, Iqbal et al. (2023) examine Islamic banks and established a strong link between textual tone and financial performance, offering a direct precedent for our methodology.

Drawing on this theoretical and empirical foundation, we analyze the annual reports of 71 full-fledged Islamic banks in 16 countries from 2017 to 2023. These documents are selected because of their standardized disclosure format, managerial authorship, and accessibility, making them an appropriate medium for sentiment extraction. Five sentiment models—TextBlob, Valence Aware Dictionary and sentiment Reasoner (VADER), Affective Norms for English Words (AFINN), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT)—are used to identify and score all segments based on AI and ML. Each model maps sentiment values on a scale from -1 to $+1$. The lexicon-based techniques rely on predefined word dictionaries (Hutto & Gilbert, 2014; Jiang et al., 2023; Vought et al., 2024), whereas the LSTM and BERT models incorporate contextual and semantic depth (Choudhary & Arora, 2024; Hochreiter & Schmidhuber, 1997). The LSTM model is ultimately selected to construct the sentiment indicators, given its superior performance in classifying sentiment in financial texts about the Islamic banking context.

After the textual data are processed (e.g., deleting irrelevant symbols and ensuring consistent tokenization), each model is trained and validated using cross-validation, with precision, recall, F1 scores, and accuracy reported for negative, neutral, and positive classes (see Fig. 1). As reflected in Panel A in Tables 1 and 2, the two deep learning methods (LSTM and BERT) generally outperform the lexicon-based alternatives regarding classification accuracy, particularly for positive sentiment. Drawing on these comparative findings, we retain the sentiment score from whichever model achieves the highest F1 score and accuracy for each bank-year observation. Consequently, we select LSTM to derive the AI and ML sentiment scores for each bank-year observation. Although LSTM and BERT consistently outperform the lexicon-based approaches in capturing overall sentiment, LSTM achieves more robust and stable classification metrics across multiple test splits, thus making it the most suitable choice for our subsequent analysis.

To construct the final variables, we average the LSTM-derived sentiment scores, from -1 (strongly negative) to $+1$ (strongly positive), for all text segments, referencing AI or ML in each annual report. This yields two key metrics.

- AI sentiment score**, which captures the mean LSTM sentiment for text blocks with mentions of AI,

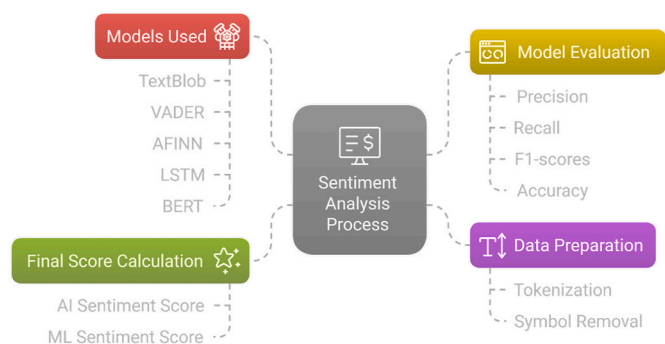


Fig. 1. Sentiment analysis process.

Table 1
Sentiment analysis results using five models.

Panel A. Word AI text						
Model	Class	Precision	Recall	F1 Score	Support	Accuracy
TextBlob	Negative	0.00	0.00	0.00	0	0.87
	Neutral	0.94	0.92	0.93	681	
	Positive	1.00	0.26	0.42	57	
	Macro avg	0.65	0.39	0.45	738	
	Weighted avg	0.94	0.87	0.89	738	
VADER	Negative	0.00	0.00	0.00	0	0.86
	Neutral	1.00	0.85	0.92	681	
	Positive	0.36	0.98	0.52	57	
	Macro avg	0.45	0.61	0.48	738	
	Weighted avg	0.95	0.86	0.89	738	
AFINN	Negative	0.00	0.00	0.00	0	0.88
	Neutral	1.00	0.87	0.93	681	
	Positive	0.42	0.95	0.58	57	
	Macro avg	0.47	0.61	0.50	738	
	Weighted avg	0.95	0.88	0.91	738	
LSTM	Negative	0.97	0.99	0.98	141	0.96
	Positive	0.67	0.29	0.40	7	
	Macro avg	0.82	0.64	0.69	148	
	Weighted avg	0.95	0.96	0.95	148	
BERT	Negative	0.00	0.00	0.00	0	0.85
	Neutral	1.00	0.84	0.92	681	
	Positive	0.36	0.95	0.52	57	
	Macro avg	0.45	0.60	0.48	738	
	Weighted avg	0.95	0.85	0.89	738	

Panel B. Word ML text						
Model	Class	Precision	Recall	F1 Score	Accuracy	
TextBlob	Negative	0.0	0.0	0.0	0.94	
	Neutral	0.96	0.98	0.97		
	Positive	1.0	0.48	0.65		
	Macro avg	0.65	0.49	0.54		
	Weighted avg	0.96	0.94	0.95		
VADER	Negative	0.0	0.0	0.0	0.95	
	Neutral	1.0	0.95	0.97		
	Positive	0.64	0.96	0.77		
	Macro avg	0.55	0.64	0.58		
	Weighted avg	0.97	0.95	0.96		
AFINN	Negative	0.0	0.0	0.0	0.95	
	Neutral	1.0	0.95	0.98		
	Positive	0.71	0.91	0.8		
	Macro avg	0.57	0.62	0.59		
	Weighted avg	0.98	0.95	0.96		
LSTM	Negative	0.97	0.98	0.98	0.95	
	Neutral	0.0	0.0	0.0		
	Positive	0.0	0.0	0.0		
	Macro avg	0.49	0.49	0.49		
	Weighted avg	0.95	0.95	0.95		
BERT	Negative	0.0	0.0	0.0	0.95	
	Neutral	1.0	0.95	0.97		
	Positive	0.6	0.96	0.74		
	Macro avg	0.53	0.64	0.57		
	Weighted avg	0.97	0.95	0.96		

2 ML sentiment score, which captures the mean LSTM sentiment for text blocks with mentions of ML.

Additionally, to capture banks' broader sentiment on AI-driven technologies, we calculate a Combined sentiment score by taking the arithmetic mean of the AI and ML scores for each observation. Following the best practices outlined in prior sentiment-driven studies in finance (de Jesus & Besarria, 2023), these averages ensure that minor fluctuations in neutral, positive, or negative classes do not overshadow the overall sentiment profile. Hence, the final database for our main analysis contains three LSTM-based sentiment indicators—AI, ML, and

Combined—which we employ as the main independent variables in models on the relationship between technological sentiment and bank performance.

This study first applies a fixed-effect panel regression with robust standard errors and time effects to investigate how AI sentiment, ML sentiment, and a combined sentiment measure affect ROE from 2017 to 2023. The choice of fixed effects rests on diagnostic tests (including variance inflation factors and the Hausman test) that indicate the need to account for unobserved, time-invariant heterogeneity across banks. The specification includes control variables—bank size, NPL ratio, GDP growth, government regulation, and internet penetration—to account for internal and external factors that influence profitability.

Subsequently, the analysis employs spline regression and random forest to confirm nonlinear relationships and provide a robustness check. The spline regression, implemented with R package splines (Perperoglou, Sauerbrei, Abrahamowicz, & Schmid, 2019; Schuster, Rijnhart, Twisk, & Heymans, 2022), is used to capture potential individual effects of the independent variables on ROE that a standard linear approach might overlook. After identifying these nonlinearities, we use a **random forest** algorithm to further explore complex functional forms and interactions (Breiman, 2001; Breiman, Cutler, Liaw, & Wiener, 2018). The data preparation involves imputation of the mean for missing values and min-max scaling of continuous predictors, followed by splitting the dataset into training (70%) and testing (30%) subsets with random sampling.

The random forest model comprises 500 decision trees built using bootstrap samples of the training data. At each tree node, a random subset of predictors is selected to minimize correlation among the trees (Leventesi & Piscopo, 2020). The algorithm seeks to reduce the mean squared error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where y_i is the observed value of sample i and $\hat{y}_i$ is the predicted value. The final prediction of the random forest model is given by:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^M \hat{y}_{T_m}$$

where M is the number of decision trees, and $\hat{y}_{T_m}$ is the prediction from tree T_m . Variable importance is assessed using the %IncMSE method, which measures the increase in MSE when a predictor's values are permuted, calculated as:

$$\%IncMSE(X_j) = \frac{MSE_{permuted} - MSE_{original}}{MSE_{original}}$$

Model performance is evaluated using three metrics, including root mean squared error (RMSE), mean absolute error (MAE), and R^2 , calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the observed values. These metrics provide a comprehensive assessment of the model's predictive accuracy.

Partial dependence plots (Greenwell, 2017) illustrate the marginal effects and interactions of the sentiment and control variables on ROE.

Table 2
Descriptive statistics.

	Mean	Min	Max	SD	Skewness	Kurtosis
Return on equity	12.576	−14.560	72.400	9.029	2.719	18.791
AI sentiment score	4.013	−1.000	39.000	6.640	2.006	7.337
ML sentiment score	2.301	−1.000	22.000	5.014	2.319	7.582
Combine score	3.157	−0.500	30.000	5.243	1.932	6.597
Bank asset growth (size proxy)	17.556	−9.090	182.100	22.461	3.076	17.204
Nonperforming loan ratio	3.632	0.040	16.780	3.394	1.568	5.287
GDP growth rate	1.857	−34.204	35.834	5.117	−0.406	20.504
Government regulation index	0.250	−1.156	1.613	0.615	−0.519	2.507
Internet penetration (IP) rate	83.087	13.780	100.000	23.373	−1.604	4.325

By combining spline regression to detect nonlinear relationships and random forest to capture higher-order interactions, this robustness analysis offers a comprehensive assessment of how AI and ML sentiment are related to profitability in Islamic banking (Orlenko & Moore, 2021; Strobl, Malley, & Tutz, 2009).

3.2. Model

This study incorporates a variety of influential factors other than the sentiment variables to thoroughly examine their effect on bank profitability, measured by ROE. In particular, recognized drivers of bank performance—such as **NPLs**, **regulatory capital** (the ratio of capital to risk-weighted assets), **GDP growth**, and **government regulation**—are included as control variables. To formalize these relationships, the baseline model is:

$$ROE_{it} = \beta_0 + \delta_1(\text{Sentiment}_{it}) + \gamma X_{it} + \varepsilon_{it},$$

where i is a bank and t is a year, (Sentiment_{it}) is one of the three main independent variables (i.e., **AI**, **ML**, or the **Combined** sentiment score), and X_{it} is a vector of control variables—**bank size**, the **NPL ratio**, **GDP growth**, **government regulation**, and **internet penetration**. β_0 is the intercept, δ_1 are the coefficients to be estimated, and ε_{it} is the error term.

To explore the potential moderating role of **GDP growth**, an interaction term is added:

$$ROE_{it} = \beta_0 + \delta_1(\text{Sentiment}_{it}) + \gamma X_{it} + \psi(\text{Sentiment}_{it} \times \text{GDP Growth}_{it}) + \varepsilon_{it},$$

where ψ is the coefficient of the interaction between the sentiment score and GDP growth.

Furthermore, the study investigates the mechanism through which AI- or ML-related sentiment scores lead to changes in ROE by incorporating a mediating variable, **ICT development**, denoted here as MV_{it} . Following Baffour Gyau et al. (2024), the mediation analysis is performed using two equations:

$$MV_{it} = \beta_0 + \delta_2(\text{Sentiment}_{it}) + \gamma X_{it} + \varepsilon_{it}$$

$$ROE_{it} = \beta_0 + \delta_3(\text{Sentiment}_{it}) + \phi MV_{it} + \gamma X_{it} + \varepsilon_{it}.$$

where ϕ is the coefficient for the indirect effect of the sentiment scores on ROE through ICT development, MV_{it} .

Lastly, to account for possible lagged effects of AI or ML sentiment on bank performance, additional regressions include sentiment variables for one to five prior periods as independent variables:

$$ROE_{it} = \beta_0 + \delta_1(\text{Sentiment}_{it-k}) + \gamma X_{it} + \varepsilon_{it},$$

with $k = 1, 2, 3, 4$, or 5 . All other variables are defined as described earlier, and this structure enables the analysis to determine whether sentiment-related impacts occur only after a certain time lag.

3.3. Data and variable descriptions

This study examines a sample of 71 full-fledged Islamic banks operating in 16 countries over the period 2017 to 2023. The availability of consistent data for these variables dictates the sample timeframe. The primary objective is to explore the influence of ROE as the dependent variable, with three main independent variables: AI sentiment score (AI), ML sentiment score (ML), and Combined sentiment score (Overall). Additionally, the study includes several control variables, including bank size (measured by total assets), NPL, GDP growth, government regulation (assessed through regulatory quality), and internet penetration (to proxy for ICT development). Appendix Table A1 lists the 16 countries, as well as the number of banks per country. Appendix Table A2 defines all the variables in the study, including their sources and levels.

3.3.1. Dependent variable: ROE

ROE is the main performance indicator in this analysis, capturing how effectively a bank generates profit relative to its equity base. Prior work has established ROE as a central gauge of bank profitability (Alalmaee, 2024; Kumar et al., 2024; Moyo & Obadire, 2024; Rehan et al., 2024). Higher ROE typically indicates that a bank manages its resources and capital efficiently, an aspect critical for competitiveness in Islamic finance.

3.3.2. Independent variables: AI, ML, and overall scores

- **AI sentiment score (AI):** This variable reflects the sentiment expressed—usually based on textual analysis—regarding AI topics that are pertinent to each bank on an annual basis. Studies applying sentiment analysis methodologies have highlighted the significance of AI in shaping profitability through cost reductions, targeted lending, and improved digital experiences (Celler, 2024).
- **ML sentiment score (ML):** This measure captures attitudes toward ML-based initiatives that banks implement, such as predictive models for credit risk or chatbots. Sentiment indicators about ML can offer insights into stakeholder trust and managerial optimism, which prior research has associated with robust financial performance (Sumathi & Sheela, 2017).
- **Combined sentiment score (overall):** Recognizing that AI and ML initiatives sometimes overlap, this variable aggregates broader text-based sentiment signals pertaining to AI-driven transformations in each bank. This kind of aggregated measure has been used in past work to give a comprehensive perspective on an institution's stance on technological adoption (Iqbal et al., 2023).

3.3.3. Control variables

- **Bank size** (growth in total assets per year): Larger banks often benefit from economies of scale, enhanced brand recognition, and greater capacity to invest in technological innovations. However, they may also face higher compliance costs and complexity (Aydemir, Atan, &

Guloglu, 2024). Including bank size helps capture these structural effects.

- Nonperforming Loan Ratio (NPL): This ratio measures the share of NPLs relative to total loans, signaling asset-quality risk. Previous research shows that elevated NPLs tend to exert downward pressure on profitability (Duong et al., 2023; Takahashi & Vasconcelos, 2024).
- GDP Growth (country-level, annual percentage): A positive macro-economic environment can foster loan demand and improve loan repayment rates, thereby boosting bank profit (Alam et al., 2021; Ledhem & Mekidiche, 2020). This variable also functions as a potential moderator in some of the empirical specifications.
- Government Regulation (Estimated Regulatory Quality): The stringency and effectiveness of regulatory standards influence banks' scope for innovation and level of market competition. Prior papers suggest that regulatory frameworks can either constrain or encourage bank profitability, depending on their design and enforcement (Ferrari, Masetti, & Ren, 2018; Nasreen et al., 2024).
- Internet Penetration (ICT Development): This study employs a measure of internet usage—often complemented by metrics such as mobile subscriptions—to capture the degree of ICT infrastructure. Earlier analyses identify ICT development as a determinant of technological adoption in financial services, with higher connectivity spurring new digital products and operational efficiency (Edwina & Mauritsius, 2024; Permatasari & Fernandes, 2024).

3.3.4. Moderating and mediating roles

Although our primary focus is the direct link between sentiment scores (AI, ML, and Overall) and ROE, we also consider potential moderation by GDP growth. Periods of strong economic expansion tend to amplify the impact of new technologies on bank revenues (Banna & Alam, 2021). In addition, internet penetration can act as a mediator: a robust ICT environment may translate positive sentiments about AI or ML into more tangible performance improvement (Md. M. Rahman, 2023).

4. Results and discussion

4.1. Descriptive statistics and correlational matrix

The descriptive statistics in Table 2 provide an overview of the key variables used in the study, highlighting their main tendencies and distributions. ROE, the primary dependent variable, has a mean of 12.576, with a wide range, −14.560 to 72.400, which suggests considerable variation in bank profitability across the sample. The high skewness (2.719) and kurtosis (18.791) indicate a nonnormal distribution, likely influenced by extreme outliers. Similarly, the sentiment scores—AI, ML, and Combined—have positive means (4.013, 2.301, and 3.157, respectively) but are skewed to the right, which suggests that higher sentiment scores are less frequent but have significant variation. Bank asset growth has the highest standard deviation (22.461),

reflecting heterogeneous growth patterns across banks, and the NPL ratio has a mean of 3.632, indicating that asset-quality issues persist for some institutions. GDP growth has a mean of 1.857, with notable negative outliers, as evidenced by its minimum, −34.204. Government regulation and internet penetration rates have relatively stable distributions, with skewness and kurtosis values that suggest less extreme deviations than for other variables. Overall, these descriptive statistics highlight the diversity in the dataset, which is critical for robust econometric modeling.

The correlation matrix in Table 3 highlights the relationships between the variables and their potential multicollinearity. ROE has significantly positive correlations with AI sentiment (0.284), ML sentiment (0.257), and the Combined sentiment score (0.303), confirming the relevance of these sentiment indicators to bank performance. Bank size also has a positive correlation to ROE (0.441), which indicates that larger banks tend to perform better. Conversely, the NPL ratio has a significantly negative correlation to ROE (−0.234), reflecting the negative impact of poor asset quality on profitability. Strong intercorrelations are found among the sentiment variables—AI and ML (0.612), AI and Combined (0.926), and ML and Combined (0.865)—indicating that these measures have substantial commonality. Government regulation and internet penetration rates have mixed associations; for example, regulation is negatively correlated with ROE (−0.191) and size (−0.223), whereas internet penetration is weakly associated with ROE (−0.0413). These patterns emphasize the importance of disentangling direct and mediated effects in the subsequent analyses to ensure the validity of the findings.

4.2. Baseline results and moderating effects

Table 4 lists the baseline findings on how AI, ML, and Combined sentiment scores affect banks' ROE. In Column (1), the coefficient for the AI sentiment score is 0.286 and significant at the 5 percent level, while in Column (2) ML has a coefficient of 0.313 ($p < 0.05$). In Column (3), the Combined sentiment score has a coefficient of 0.376 ($p < 0.05$). These results imply that higher positive sentiment about AI- and ML-related initiatives coincides with improved ROE. One plausible explanation is that advanced analytics and risk assessment tools enable banks to detect credit and operational risks more effectively, thereby decreasing defaults and losses (Karmagatri, Aziz, Asih, & Jumri, 2023). In addition, AI-powered chatbots, virtual assistants, and recommendation systems enable personalized offerings, enhanced customer engagement, and new revenue streams (Hassan, 2023; Rane, 2023). Over time, banks that adopt robust AI strategies can achieve a competitive edge, attracting a larger market share and reinforcing profitability (Hu & Wu, 2023; Moro-Visconti, 2024). These outcomes align with those of Shiyab et al. (2023), who demonstrates that AI use improves key financial indicators, highlighting the transformative potential of these innovations.

Conversely, the NPL ratio has a consistently negative and significant effect on ROE at the 5 percent level, with coefficients from −1.107 to

Table 3
Correlation matrix.

	ROE	AI	ML	COMBINE	SIZE	NPL	GDPG	REG	IP
ROE	1								
AI	0.284**	1							
ML	0.257**	0.612**	1						
COMBINE	0.303**	0.926**	0.865**	1					
SIZE	0.441**	0.144**	0.0290	0.105	1				
NPL	−0.234**	−0.142**	−0.153**	−0.163**	−0.150**	1			
GDPG	0.165**	0.110*	0.0987	0.117*	0.175**	0.0139	1		
REG	−0.191**	0.0875	0.145**	0.125*	−0.223**	−0.194**	−0.137**	1	
IP	−0.0413	0.155**	0.135**	0.162**	−0.168**	−0.350**	−0.173**	0.792**	1

Notes: * $p < 0.1$, ** $p < 0.05$. ROE, return on equity; AI, artificial intelligence sentiment; ML, machine learning sentiment; COMBINE, combined AI and ML sentiment; SIZE, bank asset growth (size proxy); NPL, nonperforming loan ratio; GDPG, GDP growth rate; REG, government regulation index; IP, internet penetration rate.

Table 4

Baseline regression results (ROE as dependent variable).

	(1)	(2)	(3)
	AI	ML	COMBINE
AI sentiment score	0.286** (0.121)		
ML sentiment score		0.313** (0.118)	
Combined score			0.376** (0.146)
Bank asset growth (size proxy)	0.075 (0.075)	0.090 (0.082)	0.077 (0.075)
Nonperforming loan ratio	−1.175** (0.373)	−1.107** (0.345)	−1.153** (0.359)
GDP growth rate	0.120 (0.072)	0.131* (0.075)	0.118 (0.071)
Government regulation index	−11.739** (5.618)	−11.268* (5.608)	−11.909** (5.681)
Constant	17.261** (2.449)	17.057** (2.471)	17.154** (2.399)
Observations	234	234	234
Time effects	Yes	Yes	Yes
Robust	Yes	Yes	Yes
AIC	1481.938	1488.136	1481.359

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$.

−1.175. This finding indicates that higher default rates undermine profitability by reducing interest income, increasing the provisioning for loan losses, and raising capital charges (Rahaman & Sur, 2021; Thornton & Di Tommaso, 2021). Similar conclusions were drawn by Duong et al. (2023), who report that each percentage point increase in NPLs erodes returns in Vietnamese banks, and by Takahashi and Vasconcelos (2024) in the Brazilian banking system. As NPLs rise, banks must channel more resources to loss provisioning, weakening net income, and, ultimately, capital adequacy (Ozili, 2020). Poor loan quality can also reduce investor confidence, further dampening profitability.

In terms of macroeconomic indicators, GDP growth has a marginally significant positive effect in Column (2), offering partial evidence that broad-based economic expansion boosts ROE. Banks in a thriving economy often observe increases in lending, in consumer demand, and in investment opportunities, which may bolster interest income and diversify revenue streams (Kar & Swain, 2014; Wang, Yang, Tang, & Wei, 2024). This aligns with the findings of studies showing that robust economic conditions promote stronger bank performance (Chhaidar et al., 2023). Nevertheless, other papers have documented a counter-intuitive association in which GDP growth compresses certain profitability metrics such as net interest margins (Robin, Salim, & Bloch, 2018). Factors such as competitive lending markets and regulatory interventions might help explain these variations.

Government regulation has a negative and statistically significant relationship with ROE, indicating that stringent oversight can reduce bank profitability. Regulation constrain banks' discretion over interest rates, lending terms, and product diversification, potentially reducing net interest margins and limiting profit-generating opportunities (Ferrari et al., 2018; Haque, 2019). Additionally, heavier regulatory burdens may raise compliance costs, thereby cutting into earnings and reducing returns on equity. This observation is consistent with that of Batae et al. (2021), who find that tighter governance measures, although beneficial for systemic stability, can negatively affect profit indicators at European banks.

In Columns (1) to (3), the control variables reflect stable trends that align with those in prior studies. Growth in bank assets—a proxy for size—has no consistent significance, which suggests that scale economies might not always translate into higher returns when examined together with AI and ML sentiment. Together, these empirical results emphasize the importance of technology adoption, efficient loan management, conducive macroeconomic settings, and balanced regulatory

environments in shaping Islamic banks' profitability.

In Table 5, adding the interaction terms in Columns (1), (2), and (3) offers additional insights into how AI, ML, and Combined sentiment scores interact with GDP growth in affecting bank profitability. In Column (1), the AI sentiment score is positive and significant despite a slight reduction from the baseline, whereas the interaction term (AI_GDPG) has a positive coefficient. This pattern indicates that banks can achieve the highest ROE when AI initiatives are deployed in an expanding economy, likely because economic growth bolsters credit demand and expands investment opportunities that reinforce AI-driven operational efficiency (Salike & Ao, 2018). At the same time, the lower main coefficient suggests that any immediate gains from AI adoption may be partly offset by upfront costs or structural changes required during implementation.

Column (2) shows similar findings for ML Sentiment Score, which is positive and significant, but the interaction term (ML_GDPG) remains statistically insignificant. Although ML investment also enhances profitability, the influence of macroeconomic expansion on ML's effectiveness may be more muted in this sample. Nonetheless, the positive sign for ML_GDPG indicates that a positive economic climate could still complement ML adoption, even if the effect does not attain conventional levels of statistical significance.

In Column (3), the Combined sentiment score once again has a strongly positive main effect on ROE, highlighted the broader advantages gained by banks from using both AI and ML approaches. However, the interaction term (COMBINE_GDPG) has a similar pattern to that in Column (2): it is positive but not significant. Together, these results suggest that although AI- and ML-related initiatives each contribute to higher profitability, the moderating role of GDP Growth varies in magnitude across the different technological dimensions. Economic conditions generally amplify technology-driven gains, but the precise degree of this enhancement differs depending on whether banks focus on AI alone, ML alone, or a combination of the two.

4.3. Mediating and lagged effects

Table 6 gives the results on the mediating role of the internet penetration rate (IP) in the relationship between banks' financial

Table 5

Moderating effects results (ROE as dependent variable).

	(1)	(2)	(3)
	AI	ML	COMBINE
AI sentiment score	0.269** (0.124)		
Bank assets growth (size proxy)	0.073 (0.075)	0.090 (0.082)	0.075 (0.075)
Nonperforming loan ratio	−1.174** (0.374)	−1.104** (0.345)	−1.150** (0.359)
GDP growth rate	0.100 (0.068)	0.113 (0.077)	0.091 (0.070)
Government regulation index	−11.536** (5.622)	−11.147* (5.596)	−11.674** (5.634)
AI_GDPG	0.008 (0.012)		
ML sentiment score		0.279** (0.109)	
ML_GDPG		0.014 (0.018)	
Combined score			0.344** (0.140)
COMBINE_GDPG			0.014 (0.016)
Constant	17.261** (2.444)	17.037** (2.476)	17.143** (2.393)
Observations	234	234	234
AIC	1483.640	1489.730	1482.836

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$.

Table 6
Mediating effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ROE with AI	IP with AI	ROE with AI & IP	ROE with ML	IP with ML	ROE With ML & IP	ROE with COMBINE	IP with COMBINE	ROE with COMBINE & IP
AI sentiment score	0.286** (0.121)	0.284** (0.078)	0.196* (0.096)						
IP rate			0.231* (0.119)			0.231* (0.134)			0.217* (0.121)
ML sentiment score				0.313** (0.118)	0.465** (0.101)	0.212** (0.100)			
Combined score							0.376** (0.146)	0.440** (0.103)	0.261** (0.111)
Constant	17.261** (2.449)	81.661** (2.204)	−2.277 (9.369)	17.057** (2.471)	80.970** (2.265)	−2.454 (10.592)	17.154** (2.399)	81.411** (2.175)	−1.190 (9.592)
Obs.	234	236	229	234	236	229	234	236	229
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	1481.938	1466.772	1428.256	1488.136	1458.671	1431.460	1481.359	1458.261	1427.980

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$.

performance (ROE) and each sentiment measure—AI, ML, and the Combined score. In Columns (1) to (3), the focus is on the AI sentiment score. Column (1) shows that the AI sentiment score has a positive and significant impact on ROE at the 5 percent level (coefficient = 0.286). In Column (2), the AI sentiment score also has a significantly positive effect on IP at the 5 percent level (coefficient = 0.284), suggesting that higher AI sentiment is associated with improvements in a bank's internet penetration environment. This finding aligns with the perspective that adopting AI-driven technologies often necessitates more sophisticated ICT infrastructure to support data analysis, automation, and customer interfaces (Naimi-Sadigh, Asgari, & Rabiei, 2022).

In Column (3), AI sentiment score and IP are both included in the model for assessing ROE. IP has a positive coefficient (0.231; $p < 0.1$), whereas AI sentiment score remains significant but slightly less so (0.196, $p < 0.1$). This pattern implies that part of AI's positive influence on ROE is due to the enhanced ICT environment—an indication of partial mediation. By investing in stronger internet infrastructure (e.g., bandwidth, digital platforms, and cybersecurity measures), banks can leverage AI more effectively, resulting in improvement in process automation, lower operating costs, and personalized services (Abdurrahman, Gustomo, & Prasetyo, 2024). These advances create a better customer experience and higher profitability (Salomi & Sam-sudeen, 2024).

Columns (4) to (6) give the results for the ML Sentiment Score. In Column (4), the ML Sentiment Score is significant at the 5 percent level (coefficient = 0.313), indicating that a more positive attitude toward ML corresponds to higher ROE. Column (5) shows that ML Sentiment Score has an even larger effect on IP (0.465, $p < 0.05$), implying that banks planning to employ ML might also emphasize developing or acquiring more robust internet-based infrastructure to manage data, train algorithms, and deploy real-time predictive tools. Consequently, in Column (6), IP has a positive coefficient (0.231, $p < 0.1$), whereas ML Sentiment Score remains positive (0.212, $p < 0.05$). The results are similar to those for AI, which suggests that ICT capabilities serve as a significant conduit through which ML sentiment translates into bank profitability.

Finally, Columns (7) to (9) list the results for the Combined score, capturing joint references to AI and ML. In Column (7), the Combined score is positively associated with ROE (coefficient = 0.376, $p < 0.05$). Column (8) shows the coefficient for the Combined score's effect on IP (0.440, $p < 0.05$), signifying that the combined adoption of AI and ML often compels banks to upgrade digital infrastructure. In Column (9), IP has a coefficient of 0.217 ($p < 0.1$), and the Combined score declines slightly in magnitude (0.261, $p < 0.05$) but retains its significance. This

finding reinforces the interpretation that ICT resources—particularly those tied to internet-enabled services—perform a mediating function, transmitting the positive impact of advanced AI and ML sentiment to bank profitability.

Table 7 reports the results on the **Combined sentiment score** with one-to five-year lags (L1_COMBINE to L5_COMBINE) as predictors of ROE. Unlike previous models that included AI and ML separately, this table focuses solely on the combined measure, in order to capture AI- and ML-related activities more comprehensively. By consolidating these sentiments into one variable, the lagged approach can better identify the effect of blended technology strategies on banks' profitability over an extended timeframe.

Column (1) shows that L1_COMBINE has a positive coefficient of 0.335, significant at the 5% level, which implies that a rise in combined AI–ML sentiment translates into higher ROE after one period. This result is consistent with the notion that banks initially benefit from improved operating processes, risk assessment, and product innovation when they adopt AI and ML in tandem. In Column (2), L2_COMBINE remains positive at 0.195 (though not statistically significant), which suggests that although the effect of combined sentiment persists, its magnitude might taper off in the second year. Column (3) indicates a slightly larger and significant coefficient (0.223, $p < 0.1$) in the third lag, implying a renewed gain from combined AI–ML strategies. This pattern might be

Table 7
Lagged effects.

	(1)	(2)	(3)	(4)	(5)
	ROE	ROE	ROE	ROE	ROE
L1_COMBINE	0.335** (0.132)				
L2_COMBINE		0.195 (0.118)			
L3_COMBINE			0.223* (0.112)		
L4_COMBINE				0.021 (0.223)	
L5_COMBINE					0.527 (0.478)
Constant	17.274** (2.615)	20.712** (4.395)	22.399** (6.154)	26.430** (6.125)	5.848 (8.654)
Observations	201	168	134	101	67
Control variables	Yes	Yes	Yes	Yes	Yes
AIC	1263.841	1061.572	842.556	605.836	358.166

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$.

due to time lags associated with the full implementation of advanced analytics or from the gradual accrual of network benefits, such as better customer data integration or refined credit models.

The results become less conclusive in Columns (4) and (5): coefficient of L4_COMBINE is slightly positive (0.021) and that of L5_COMBINE is 0.527 is higher, but not statistically significant. These findings suggest that, after three to four years, the immediate

advantages of AI–ML adoption might wane, possibly because of the industry-wide proliferation of similar technologies, rising maintenance costs, and a convergence effect as competitors catch up. This pattern aligns with prior literature indicating that initial investment in AI yields clear efficiency gains, which diminish later, as innovations become broadly adopted and no longer serve as strong differentiators.

From a strategic perspective, the sole focus on the combined measure

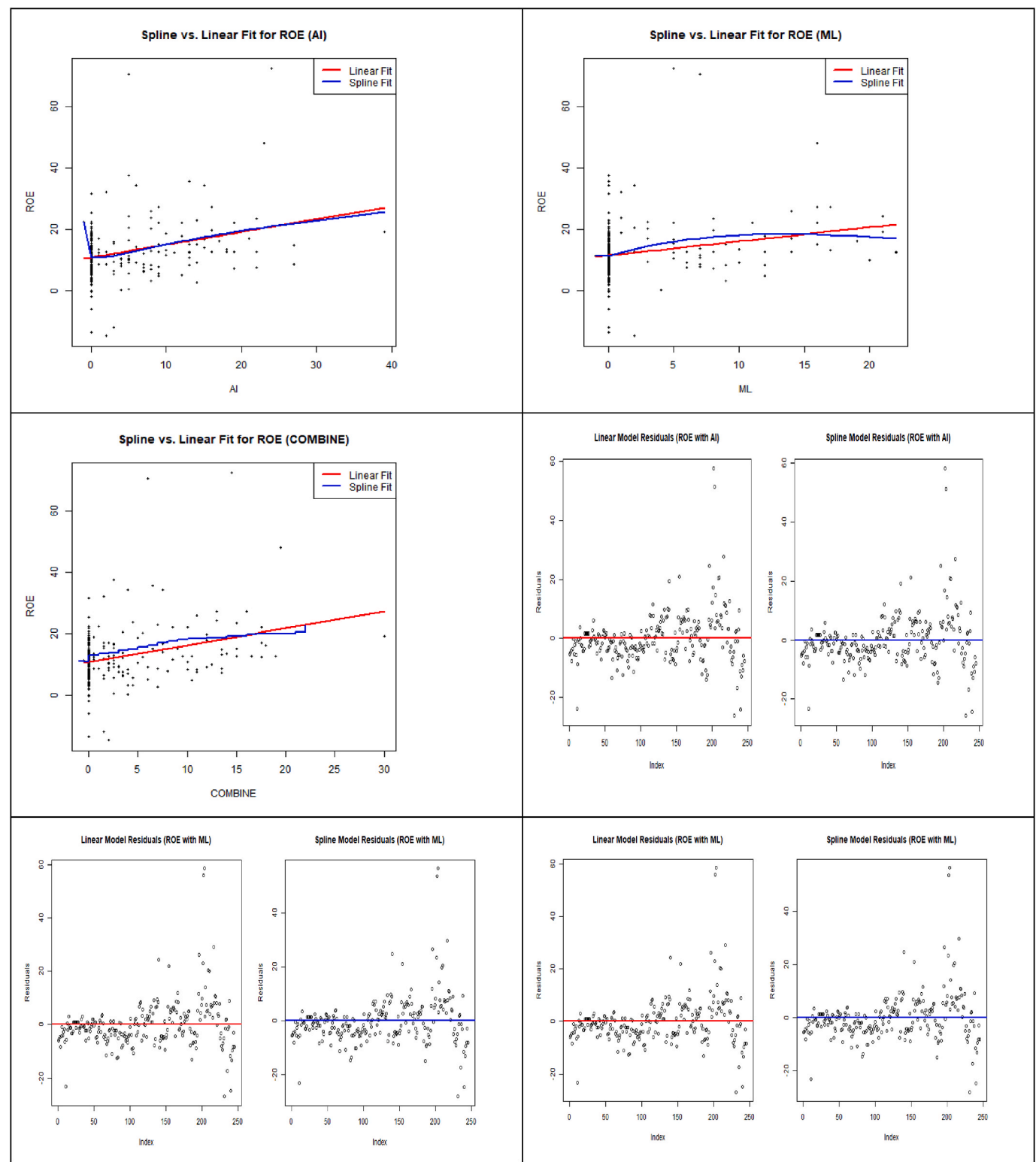


Fig. 2. Scatter plots and residual comparison for linear and spline models.

in the lagged model demonstrates the importance of adopting a combined AI–ML framework, rather than viewing them in isolation. Early gains may be due to significant improvements in decision support, automation, and customer-facing services. However, over time sustaining these gains requires banks to continually invest in system upgrades, workforce training, and data refinement. After the broader market begins to invest in similar tools, the competitive advantage might shrink,

thereby explaining the weaker or insignificant coefficients at longer lags. Moreover, overhead costs related to implementation and upkeep could erode initial profitability gains, reflecting a tipping point at which long-term expenditures begin to outpace the benefits from being a first-mover.

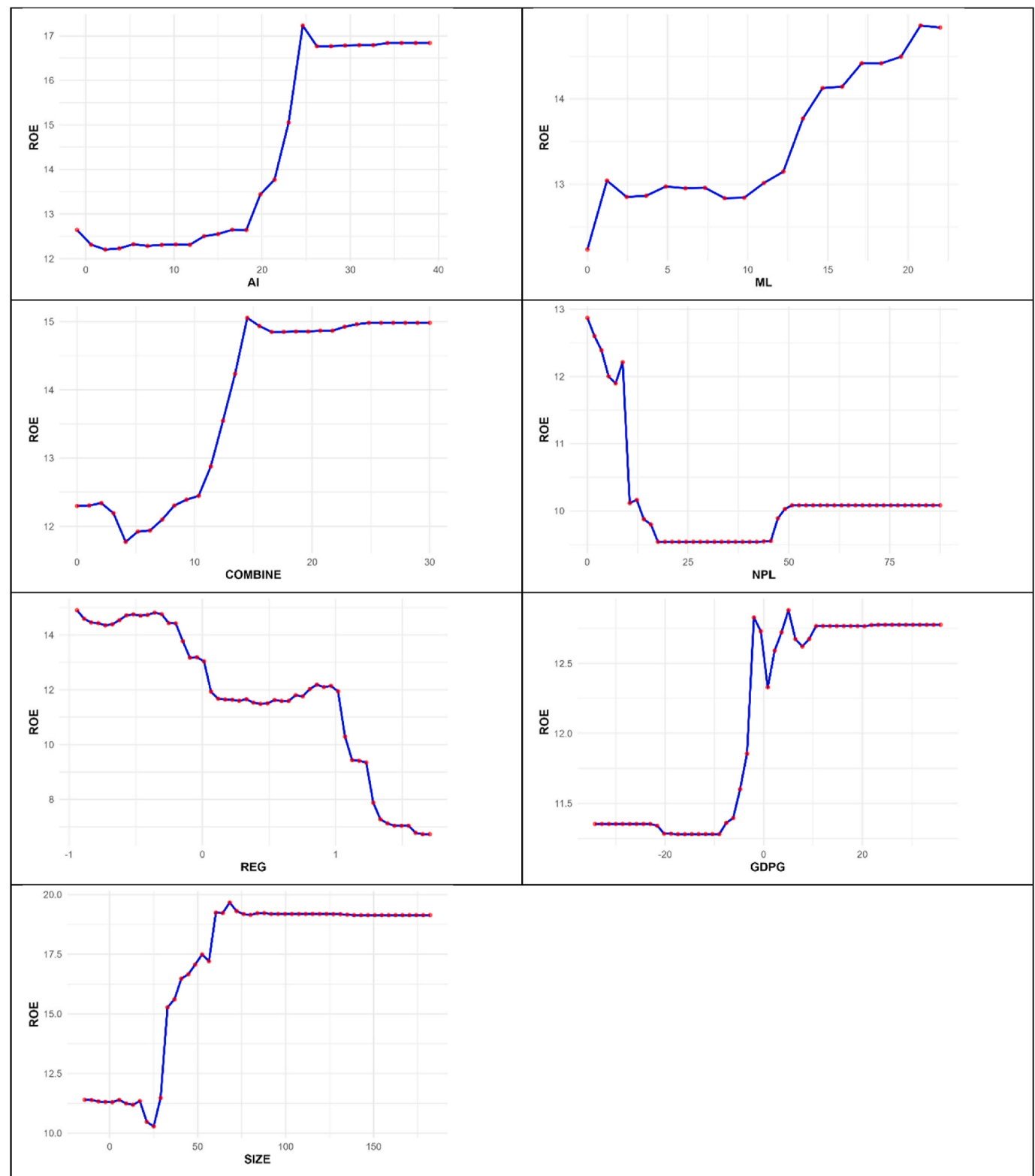


Fig. 3. Random forest partial dependence plots for ROE.

4.4. Robustness analysis

The robustness analysis, shown in Figs. 2–4 as well as Table 8, provides a comprehensive evaluation of our primary results using advanced ML methodologies, including spline regression and random forest modeling. The scatter plots and residual comparisons between linear and spline models (Fig. 2) reveal that spline models demonstrate better alignment with the observed data patterns, affirming the presence of nonlinear relationships between AI, ML, and COMBINE sentiment scores and financial performance. These findings support the decision to employ more flexible approaches for robustness testing, such as like random forest, which effectively captures nonlinear dependence and interactions.

Table 8 highlights the importance of variables from the random forest models, with and without interaction effects, emphasizing the significant contributions of COMBINE sentiment scores to ROE in Models 1 (0.0991) and 2 (0.0918). The inclusion of interaction terms, particularly COMBINE $\times$ GDPG (0.0414), offers additional insights into the amplified effects of sentiment scores when coupled with economic growth. R^2 for the two models (0.4441 and 0.4334) confirm the robustness of our primary findings, but they indicate slightly less predictive power than the fixed-effects regression results. Figs. 3 and 4 further substantiate these findings, as the partial dependence plots illustrate the positive incremental impacts of AI, ML, and COMBINE sentiment scores on ROE, as well as their synergistic interactions with GDP growth. Overall, the robustness checks confirm and extend the primary results by emphasizing the nuanced nonlinear and interactive dynamics in the sentiment–financial performance nexus.

The robustness analysis focused on ROA confirms the nonlinear relationships initially identified in the primary analysis. Appendix Figure B1 illustrates the comparative fit of linear versus spline regression models, showing that spline models provide a superior fit for capturing the subtle variations in ROA when associated with AI, ML, and Combined sentiment scores. This indicates that nonlinear modeling

Table 8
Random forest (robustness analysis, criterion ROE).

	Model 1	Model 2
AI	0.0869	0.0541
ML	0.0687	0.0710
COMBINE	0.0991	0.0918
Size	0.3335	0.2768
NPL	0.1476	0.1237
REG	0.2168	0.1724
GDPG	0.0475	0.0814
AI $\times$ GDPG	–	0.0446
ML $\times$ GDPG	–	0.0428
COMBINE $\times$ GDPG		0.0414
RMSE	8.2708	8.3497
MAE	5.1206	5.1945
R ²	0.4441	0.4334

Model 1: Variable importance without interaction effects; Model 2: Variable importance with interaction effects.

techniques are more effective for explaining the variations in financial performance influenced by sentiment measures. The random forest partial dependence plots in Appendix Figure B2 further support these findings, highlighting the differential impacts of AI, ML, and Combined sentiment scores on ROA, in addition to their interactions with GDP growth (Appendix Figure B3). The random forest results in Appendix Table B1 demonstrate that Combined sentiment score has highest predictive capability for ROA in both models, and the inclusion of interaction terms slightly raises the explanatory power ($R^2 = 0.5251$ in Model 1 and $R^2 = 0.5202$ in Model 2).

When compared to the primary results, the robustness outcomes confirm the significance of AI and ML sentiment scores, though the size of the effect for individual sentiment variables is lower in the random forest models. This indicates that, whereas linear methods capture general trends, nonlinear approaches, such as random forest, are essential for identifying more complex relationships and interaction effects. The Combined score is the most reliable predictor of financial

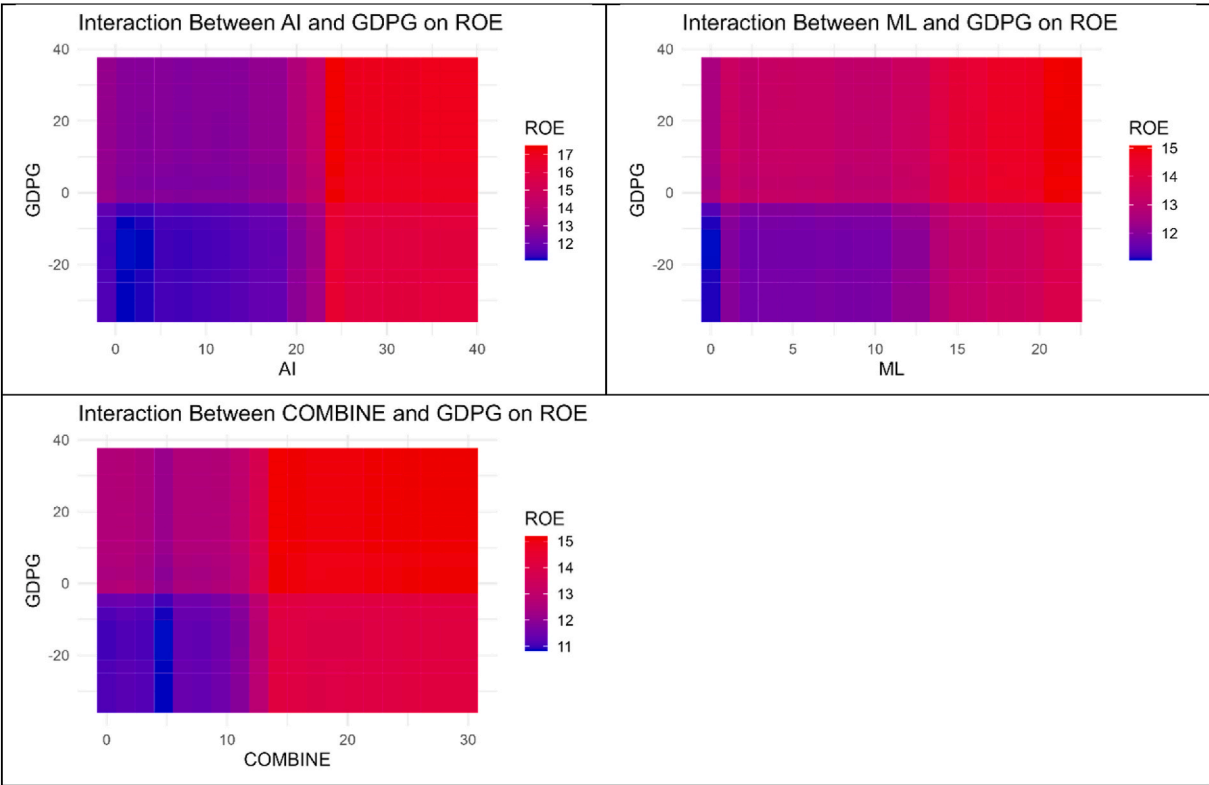


Fig. 4. 2D random forest partial dependence plots for interaction effects for ROE.

performance for both criteria (ROE and ROA), showing its robustness as a comprehensive sentiment measure. These findings highlight the importance of employing advanced methodologies, such as random forest and spline regression, to confirm and complement insights from traditional panel regression analysis. For further details, see [Appendix Figures B1 to B3](#) and [Appendix Table B1](#).

5. Conclusion, implications, limitations, and directions for future research

This study performs a comprehensive empirical investigation of the relationship between sentiment regarding AI and ML and the financial performance of Islamic banks. It uses a multiyear panel dataset covering 71 Islamic banks across 16 countries and a combination of fixed-effects regression, spline regression, and random forest models to examine whether sentiment extracted from internal bank disclosures with LSTM-based sentiment scoring predicts profitability, as measured by ROE and ROA. The analysis reveals that AI and ML sentiment scores—particularly the combined metric—are positively correlated with financial outcomes. By including lagged sentiment measures, the study shows that these effects are not immediate but, rather, unfold over multiple years and diminish over time, which signals the need for long-term strategic alignment of AI adoption with institutional performance objectives. This insight contributes to the literature by employing a dynamic perspective on the financial relevance of AI sentiment, a dimension largely absent from prior studies.

This research extends the boundaries of current scholarship in several important ways. First, whereas prior studies focus primarily on the operational benefits of AI in banking—such as improvements in efficiency, fraud detection, and compliance ([Königstorfer & Thalmann, 2020](#); [Shiyyab et al., 2023](#))—this study advances a sentiment-centered approach. It is the first to empirically validate the predictive utility of AI-related sentiment in annual reports as a forward-looking indicator of financial performance in the Islamic banking context. This contribution is significant because internal disclosures capture managerial intention, optimism, and strategic direction and have a predictive value that is not captured in externally sourced metrics. Second, the study uses ICT development as a mediating variable, confirming that digital infrastructure plays a crucial role in transmitting the effects of AI sentiment to financial outcomes. This path of mediation has not been extensively examined in Islamic finance literature and enhances the theoretical basis of the study by linking digital readiness with performance ([Aguegboh et al., 2023](#)).

Third, the study shows that macroeconomic conditions, particularly GDP growth, moderate the relationship between AI/ML sentiment and profitability. This moderating effect implies that the same level of sentiment may have different financial outcomes, depending on the economic environment, reinforcing the importance of context-sensitive strategies. This insight is consistent with the growing literature emphasizing that AI adoption outcomes are shaped by external institutional and macroeconomic conditions ([Edwina & Mauritsius, 2024](#)). The application of nonlinear techniques, such as spline regression, and ML models, such as random forest, enables the complex, nonlinear nature of these relationships to be captured in the study. Traditional linear models often overlook such interactions, but the robustness checks confirm that the Combined sentiment score is the most reliable and consistent predictor across all model specifications.

From a policy perspective, this study constructs a sentiment-informed framework tailored to Islamic banking, which varies from the generic model ([Ali, Aysan, & Mesroua, 2025](#)), to identify feasible, evidence-based strategies. The results indicate that sentiment metrics embedded in official communications act as early indicators of

institutional readiness and strategic alignment with AI and ML transformation ([de Jesus & Besarria, 2023](#); [Iqbal et al., 2023](#)). Although prior papers treat ICT infrastructure as a supportive component ([Aguegboh et al., 2023](#); [Al-Busaidi & Al-Muharrami, 2021](#)), our findings demonstrate, instead, that it is a critical mechanism through which AI sentiment is operationalized into financial performance.

Consequently, policy makers are urged to adopt integrated strategies that align digital investment with sentiment-informed AI planning, including measures to expand broadband access, strengthen cybersecurity, and enhance digital literacy ([Abdurrahman et al., 2024](#); [Edwina & Mauritsius, 2024](#)). The lagged impact of sentiment highlights the need for multiyear planning cycles, as short-term metrics might fail to capture delayed or tapering effects over time ([Baffour Gyau et al., 2024](#); [Robin et al., 2018](#); [Salomi & Samsudeen, 2024](#)). This study also pushes out the methodological frontier. The integration of ML and econometric modeling enables a more comprehensive analysis than prior studies that rely on only one methodological paradigm. Random forest, in particular, enables better predictive performance and ranking of variable importance, confirming the superiority of combined sentiment over individual AI or ML scores. This mixed-methods approach is consistent with emerging recommendations in fintech research for the use of methodological pluralism to capture multifactorial phenomena ([Iqbal et al., 2023](#)).

Nevertheless, the study has several limitations. The temporal scope is limited to the period 2017–2023, which excludes recent developments in generative AI technologies and their institutional implications. Moreover, although the study incorporates ICT development and GDP growth as a mediator and moderator variables, respectively, it does not account for other potentially influential factors, such as board composition, regulatory agility, and human capital readiness. A second limitation is that the sentiment data is derived solely from internal disclosures, which may reflect a rhetorical position or strategic optimism, rather than actual technological capability or investment. Additionally, although the sample includes banks from 16 countries, regional heterogeneity in Islamic banking systems might introduce variations that are not fully captured in our model.

Future research should address these limitations by expanding the temporal scope to incorporate more recent annual reports and by including external sentiment sources, such as media narratives, market reactions, and stakeholder feedback. Studies that compare Islamic and conventional banks would help clarify whether sentiment dynamics differ across governance models. Scholars should also consider examining how variations in the structure of sharia supervisory boards influence AI sentiment and digital transformation strategies. Further investigation into generative AI, including how it is perceived and discussed in financial disclosures, would enhance understanding of the emerging technological narratives. These recommendations would refine the predictive models and contribute to the development of a more nuanced, contextually grounded theory of AI adoption and performance in Islamic finance.

CRediT authorship contribution statement

Hassnain Ali: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Supervision, and, Project administration. **Ahmet Faruk Aysan:** Writing – review & editing, Supervision, Project administration, and, Investigation.

Acknowledgments:

None.

Appendix A

Appendix Table A1

Total number of banks per country selected for analysis

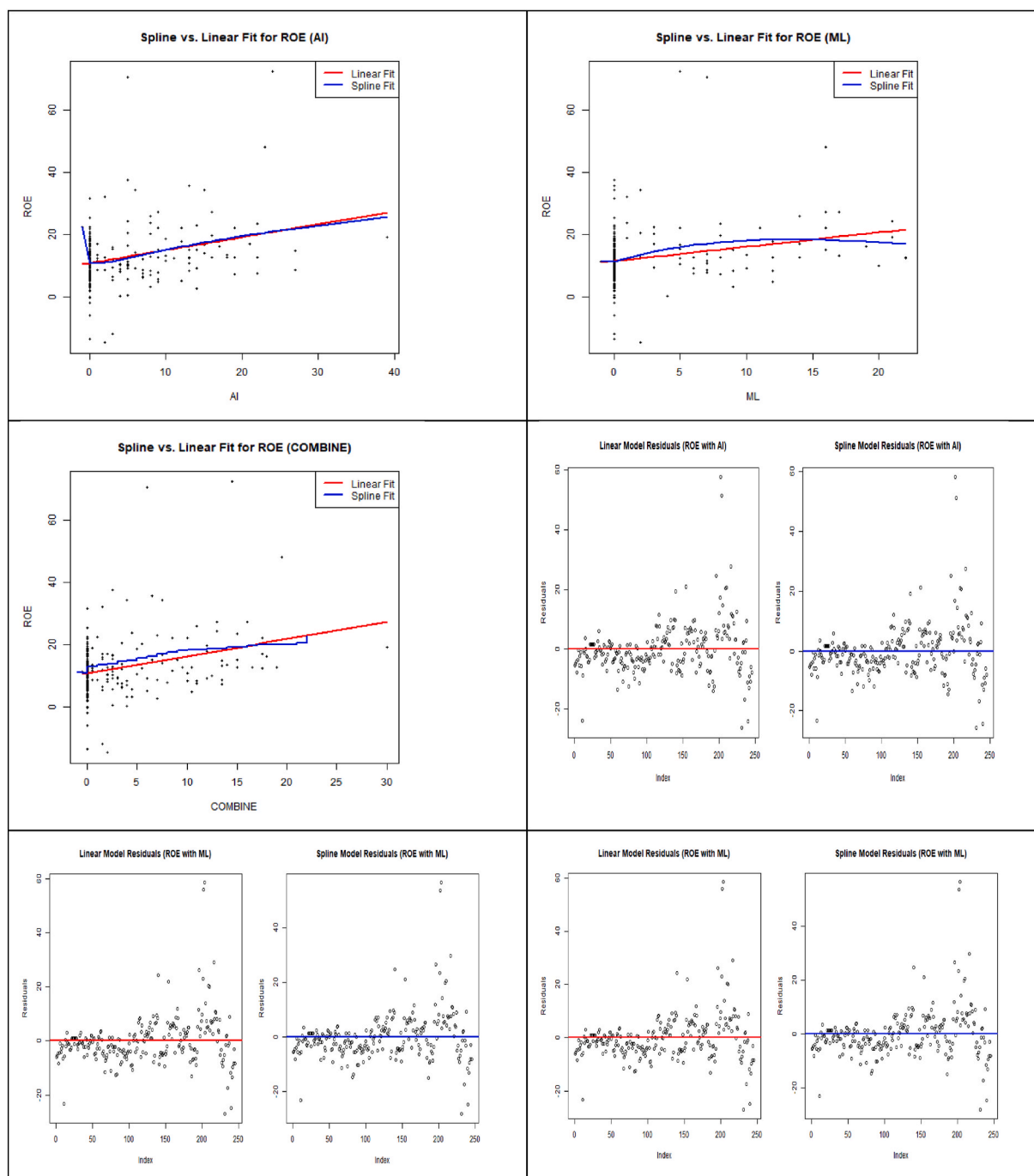
Sr. No.	Country	Number of banks
1.	Bahrain	7
2.	Bangladesh	7
3.	Brunei	1
4.	Indonesia	9
5.	Kuwait	4
6.	Malaysia	13
7.	Maldives	1
8.	Nigeria	1
9.	Oman	3
10.	Pakistan	4
11.	Qatar	4
12.	Saudi Arabia	5
13.	South Africa	1
14.	Türkiye	5
15.	UAE	4
16.	UK	2
	Total	71

Appendix Table A2

Definition of the variables

Variable name	Description	Data source	Country or bank level
Dependent variable ROE	Return on equity (ROE) is the core performance indicator for capturing how effectively a bank generates profits relative to its equity base.	Fintech connect	Bank level
Independent variables AI sentiment score	The AI sentiment score reflects the sentiment expressed regarding AI topics pertinent to each bank on an annual basis.	Annual reports (Bank's website)	Bank level
ML sentiment score	The ML sentiment score captures attitudes toward machine learning-based initiatives implemented by banks, such as predictive models for credit risk or chatbots.	Annual reports (Bank's website)	Bank level
Combined sentiment score	The combined sentiment score aggregates broader sentiment signals pertaining to AI-driven transformations at each bank.	Annual reports (Bank's website)	Bank level
Control variables Bank size	Bank size (total asset growth per year) measures the size of a bank, capturing structural effects, such as economies of scale.	Fintech connect	Bank level
Nonperforming loans ratio	The nonperforming loans ratio (NPL) gauges the share of nonperforming loans relative to total loans, signaling asset-quality risk.	Fintech connect	Bank level
GDP growth	GDP growth is a country-level variable that measures the annual percentage change in GDP, affecting macroeconomic conditions and bank profitability.	World bank	Country level
Government regulation	Government regulation (regulatory quality estimate) reflects the stringency and effectiveness of regulatory standards that influence banks' scope for innovation and competition.	World bank	Country level
Internet penetration	Internet penetration measures ICT development, capturing internet use and related metrics, such as mobile subscriptions, to assess the degree of technological adoption.	World bank	Country level
Robustness ROA	Return on assets measures a bank's profitability relative to its total assets, providing insight into how effectively a bank is using its assets to generate profit.	Fintech connect	Bank level

Appendix B



Appendix Fig. B1. Scatter plots for linear and spline models.

Appendix Table B1

Robustness test: Random forest analysis (Criterion, Financial performance, ROA)

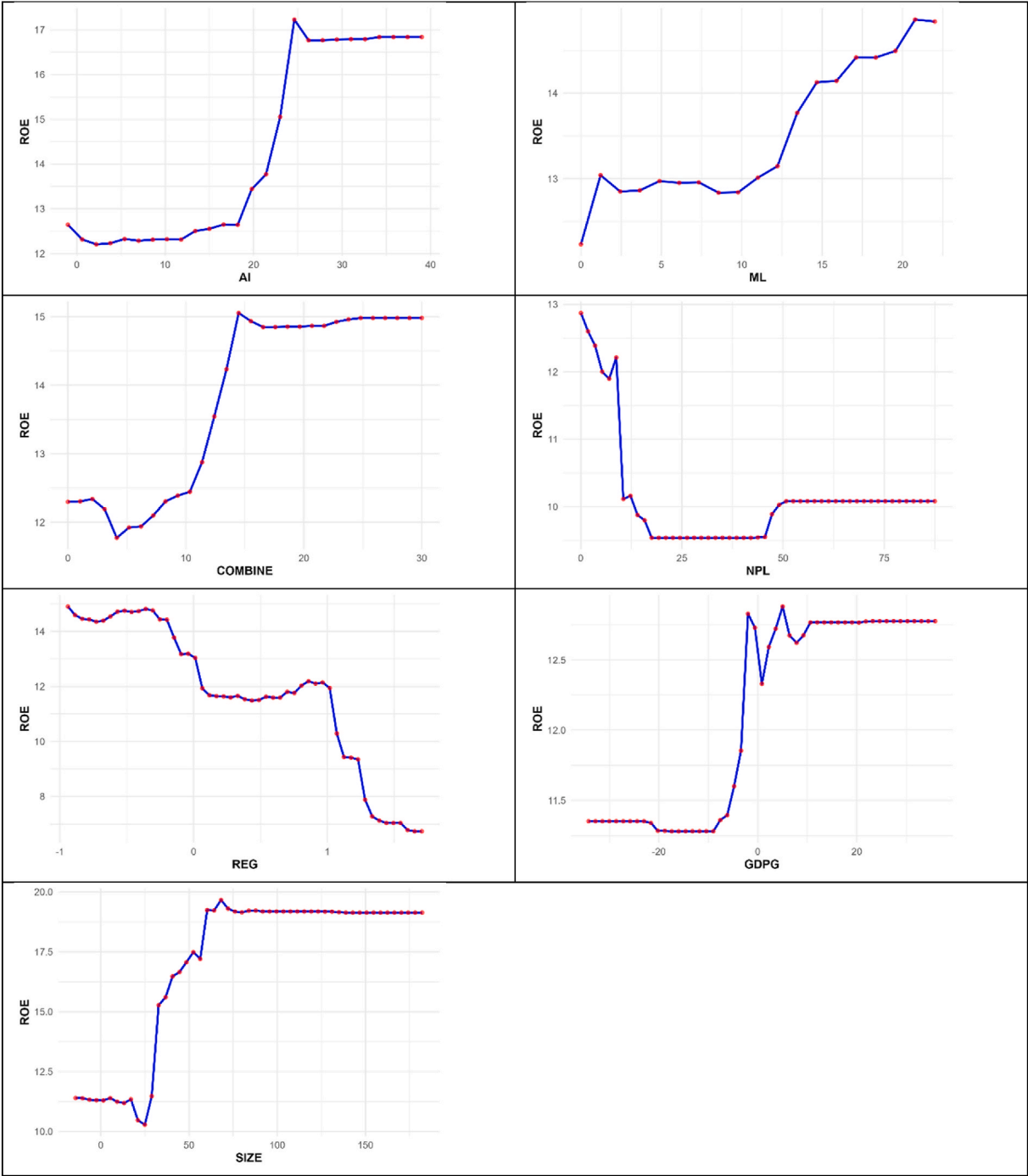
	Model 1	Model 2
AI	0.0316	0.0291
ML	0.0470	0.0400
COMBINE	0.0511	0.0299
Size	0.2117	0.1908
NPL	0.3429	0.3317
REG	0.1953	0.1600
GDPG	0.1205	0.1072
AI × GDPG	–	0.0470

(continued on next page)

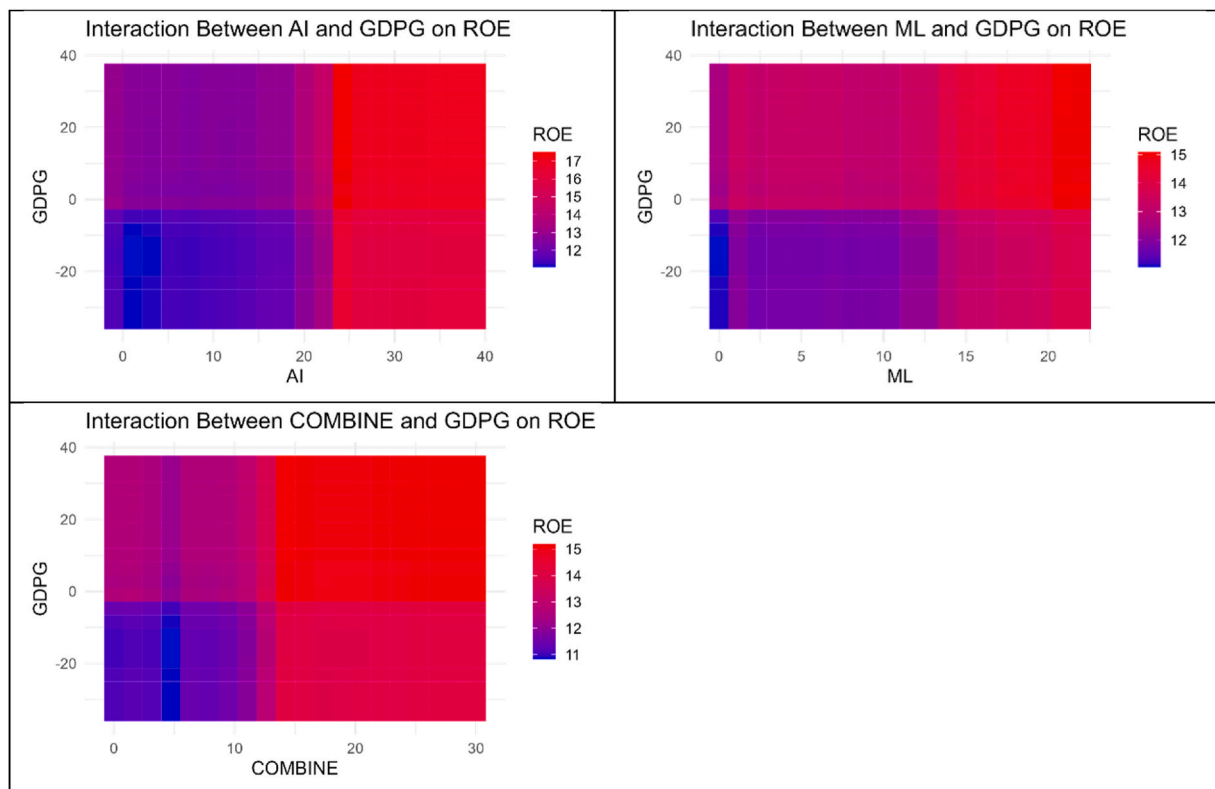
Appendix Table B1 (continued)

	Model 1	Model 2
ML × GDPG	–	0.0234
COMBINE × GDPG		0.0409
RMSE	0.9354	0.9402
MAE	0.5817	0.5834
R ²	0.5251	0.5202

Notes: Model 1: Variable importance without interaction effects; Model 2: Variable importance with interaction effects.



Appendix Fig. B2. Random forest partial dependence plots for ROA.



Appendix Fig. B3. 2D random forest partial dependence plots for interaction effects.

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