

From black box to bottom line: the role of AI disclosure in bank performance in Malaysia

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Abstract

Purpose – The study examines the role of AI disclosure in the Malaysian banking sector by investigating its effects on profitability and operational efficiency. Grounded in signalling and stakeholder theories, it considers how AI transparency relates to financial performance within an evolving banking environment.

Design/methodology/approach – Using panel data from 32 Malaysian commercial banks over the period 2019 to 2023, the study applies the two-step GMM estimator and quantile regression to examine both the overall and distributional effects of AI disclosure.

Findings – The findings show that AI disclosure is positively linked with profitability, as shown in ROA and ROE, and negatively connected with CTI, indicating better cost efficiency. The quantile regression further shows that the cost-saving effects of AI disclosure are more visible among both efficient banks and banks facing higher cost pressures.

Research limitations/implications – The study is based on quantitative analysis within a single-country context and does not include cross-market comparisons. Its five-year period may also limit the ability to observe the longer-term financial effects of AI disclosure.

Practical implications – The findings suggest that banks should treat AI disclosure as a strategic practice that can strengthen investor confidence, improve cost efficiency, and build stakeholder trust. For policymakers, the results highlight the importance of developing a balanced regulatory framework that encourages innovation while preserving financial stability, transparency, and inclusiveness.

Originality/value – The study contributes to the literature by applying signalling and stakeholder theories to explain the financial implications of AI disclosure in banking. It also introduces a structured and measurable approach to measuring AI transparency, showing how disclosure may strengthen financial resilience, operational efficiency, and investor confidence in a developing economy setting.

Keywords Artificial intelligence, Banking performance, AI disclosure, Profitability, Cost efficiency, Developing economies

Paper type Research article

1. Introduction

Artificial intelligence (AI) has progressed from information processing to driving change in banking operations, product design and risk management (Mithas *et al.*, 2022). By automating tasks and supporting personalised services, AI can improve customer experience, efficiency, productivity and financial resilience (Moharrak and Mogaji, 2024). It can also reduce costs and losses through automated processing, fraud detection and credit risk assessment (Adewumi *et al.*, 2024), while supporting revenue growth and customer retention (Mogaji and Nguyen, 2022). However, its effect on financial performance remains debated. Although AI may improve profitability through better customer experience and risk management, traditional banks still dominate due to established customer bases, regulatory expertise and financial stability. Furthermore, banks still face challenges related to AI implementation costs and regulatory barriers, while concerns over AI transparency, ethics and accountability continue to



grow (Ridzuan *et al.*, 2024). A KPMG (2021) survey of 751 business leaders found that 42% linked AI to data privacy or cybersecurity risks, and 94% supported stronger government regulation. Thus, although clearer AI disclosure may strengthen governance and trust, its relationship with financial performance remains unclear, especially in emerging banking markets such as Malaysia.

Malaysia presents a strong case for examining AI-driven banking within a developing economy. The country records high digital adoption, with Internet banking penetration at 140% and mobile banking at 97% (Bank Negara Malaysia, 2023). Its robust regulatory framework (Razali *et al.*, 2022), well-structured financial system (Kuular, 2020), and support through the Malaysia AI Roadmap (2021–2025) make it a useful context for studying AI integration and a relevant reference for other developing economies, especially in Southeast Asia and the Middle East, where AI adoption in banking is still evolving. Despite growing attention to AI integration, limited studies have examined how transparency in AI disclosures relates to financial outcomes in banking, particularly in developing economies. Banks are among the earliest and most intensive adopters of AI (Herrmann and Masawi, 2022), yet they operate in a highly regulated environment where innovation must be balanced with compliance and stakeholder trust (Rahman *et al.*, 2021). It makes AI disclosure a useful perspective for understanding how banks communicate technological capability while maintaining credibility. In the present study, AI disclosure refers to how banks report their use of AI in their operations, including where AI is applied, how it supports decision-making, the governance mechanisms in place, and the related risks, as communicated through annual or integrated reports (Josh *et al.*, 2025). Although related, AI adoption and AI disclosure are conceptually distinct. AI adoption refers to the actual implementation and use of AI technologies in banking operations, whereas AI disclosure refers to how such use is communicated to key stakeholders through annual or integrated reports. Accordingly, the study examines AI disclosure as a reporting-based indicator of banks' communicated AI engagement rather than a direct measure of actual AI adoption or implementation depth.

The disclosure issue is especially relevant in developing economies such as Malaysia, where AI adoption is progressing, but regulatory maturity, infrastructure and disclosure culture continue to evolve (Ramachandaran *et al.*, 2025). In contrast, developed markets are increasingly standardising AI reporting through ESG-linked frameworks, such as the EU AI Act, the ESG Ratings Regulation, and U.S. guidance. In such settings, AI disclosure functions both as a strategic signal of competitiveness and as a means of legitimising innovation. However, although earlier studies mainly examine AI adoption and operational performance gains (Venkatesh *et al.*, 2023), the role of disclosure in shaping profitability and cost efficiency has received limited attention. Hence, the study examines whether AI disclosure influences bank profitability and cost efficiency, and whether these effects vary across banks with different performance levels. By focusing on disclosure rather than adoption, the study responds to growing regulatory and stakeholder demands for transparency while extending earlier studies on AI-driven banking performance.

The remainder of the paper is organised as follows. Section 2 reviews the literature on AI disclosure in banking, outlines signalling and stakeholder theory, and develops the hypotheses. Section 3 describes the dataset, construction of the AI Disclosure Index (AIDI), variable definitions, and the econometric methods, together with diagnostic checks. Section 4 presents the empirical results. Section 5 discusses the findings. Section 6 outlines the theoretical, managerial, and policy implications. Section 7 presents the limitations and directions for future research. Section 8 concludes the study.

2. Literature background

The use of AI in banking is receiving growing academic attention, especially for its effects on operational effectiveness and efficiency compared with traditional banking models. AI technologies such as machine learning, predictive analytics, and robotic process

automation are widely seen as improving efficiency, lowering costs, and strengthening customer engagement (Zaylani, 2024). They may also improve ROA through better resource allocation and increase ROE through personalised services and algorithmic decision-making (Huang, 2024). However, these gains remain context-dependent and are determined by implementation scale, data quality, and compatibility with legacy systems. In developing economies, high investment costs, skills shortages, and limited digital infrastructure may weaken short-term profitability. Although AI can reduce CTI by automating labour-intensive processes, savings may be counterbalanced by compliance and technology maintenance costs. Hence, its effects on ROA, ROE, and CTI remain conditional in recent banking studies.

Past studies on ESG and FinTech disclosures provide a useful basis for understanding transparency in emerging domains. ESG disclosure frameworks improve accountability in governance, strategy, and performance (Eng *et al.*, 2021; Yasmine and Kooli, 2022), but give limited attention to technological innovation in banking. FinTech disclosure research similarly highlights data ethics, privacy, and digital responsibility (Aldboush and Ferdous, 2023; Amir *et al.*, 2025), yet often treats transparency as a compliance issue rather than linking it to financial outcomes. These studies leave a gap in understanding how banks disclose AI information and whether such transparency affects financial performance, which the present study addresses through the AIDI. The issue is especially relevant in developing economies such as Malaysia, where infrastructural, regulatory, and market conditions differ from more digitalised contexts.

Signalling theory (Spence, 1973) suggests that firms use disclosure to reduce information asymmetry and send favourable signals to investors and stakeholders. It is consistent with the voluntary disclosure framework, under which signalling theory is commonly situated. In banking, AI disclosure can signal technological capability, innovation in risk management, digital resilience, and efficiency gains, thus firming market confidence (Shiyyab *et al.*, 2023). It can also help distinguish technologically advanced banks and address stakeholder concerns over algorithmic bias, cybersecurity, and governance transparency. Furthermore, credible AI disclosure may improve reporting quality, lower information asymmetry and funding costs, and support profitability measures such as ROA and ROE (Alzaghoul and Alsharari, 2024; Al-Okaily, 2025b). Moreover, it may signal operational efficiency when banks disclose automation benefits, cost savings, and AI applications, which can contribute to a lower cost-to-income ratio (CTI) and stronger financial sustainability (Al-Okaily, 2025a).

Stakeholder theory (Freeman, 1984) stresses balancing the interests of regulators, customers, employees, and the wider community. In banking, AI disclosure is important because institutions are subject to strict regulatory oversight. Transparent disclosure can indicate compliance and strengthen relationships with regulators (Lee, 2020), which may support financial performance through greater efficiency, lower compliance costs, higher ROA, and lower CTI. Extensive disclosure of AI use in customer service, fraud detection, and personalised financial management can also increase customer trust, satisfaction, and retention, contributing to higher ROA and ROE (Alzaghoul and Alsharari, 2024). More broadly, AI disclosure signals technological responsibility, ethical awareness, and responsiveness to stakeholder expectations, which can build customer loyalty and market confidence and support sustainable profitability (Aldboush and Ferdous, 2023).

Taken together, signalling theory and stakeholder theory propose that AI disclosure is not merely a compliance requirement but also a strategic asset with financial implications. Although signalling theory focuses on its role in attracting investment and building market confidence, stakeholder theory highlights its reputational, regulatory, and ethical importance for financial stability. Based on these perspectives, the study proposes the following hypotheses.

- H1. AI disclosure has a positive relationship with bank profitability (ROA and ROE)
- H2. AI disclosure has a negative relationship with the cost-to-income ratio (CTI)
- H3. The effect of AI disclosure on financial performance varies across banks with different performance levels

3. Methodology

3.1 Research design, data, and sample

The study adopts a quantitative approach using secondary data to examine the relationship between AI disclosure and the financial performance of Malaysian banks. Covering 2019 to 2023, it emphasises the early stage of AI integration in Malaysian banking, indicating its gradual adoption across the sector (Rahman *et al.*, 2021). Financial data for ROA, ROE, and CTI are obtained from Bloomberg. Although Malaysia has 41 commercial banks, data availability limited the final sample to 32 banks, representing 78% of the sector and producing a balanced panel of 160 observations.

3.2 Measurement of variables and construction of the AIDI

The study measures AI disclosure through content analysis of annual reports from sampled banks. Annual reports are used because they are the main channel for communicating strategic information to external stakeholders, are prepared under regulatory and auditing standards, and are more reliable for evaluating banking practices (Tilt, 1994; Lui and Haniff Zainuldin, 2024). AI disclosure is measured using an unweighted index based on the frequency of AI-related terms in the reports (Seebeck and Kaya, 2022). To improve construct validity, the keyword list was refined through consultation with two researchers in AI-driven banking (Zainuldin and Lui, 2021) and includes terms such as artificial intelligence, machine learning, predictive analytics, chatbots, deep learning, natural language processing, neural networks, algorithmic trading, credit scoring algorithms, and AI-related risk management. These terms encompass both core technologies and banking applications, allowing the index to capture the breadth of AI disclosure across Malaysian commercial banks.

To standardise AI disclosure levels across banks, the study calculates an AIDI using a Z-score conversion that normalises the total word count for AI terms, enabling meaningful bank comparisons. The AIDI is formulated as follows:

$$AIDI_i = \frac{X_i - \mu}{\sigma}$$

Where $AIDI_i$ represents the AI disclosure index for bank i , X_i denotes the total number of

AI words disclosed by bank i , μ is the mean number of AI words across all banks, and σ is the standard deviation of AI word counts.

Although various disclosure measures exist, the AIDI provides an objective and consistent indicator based on text frequency. Weighted indices examine materiality across governance, strategy, and risk dimensions (Rahman and Masum, 2021), while text-mining and sentiment-based methods assess tone and context (Zucco *et al.*, 2019), but these approaches often involve subjective weighting or substantial computational and linguistic demands. In comparison, the unweighted, frequency-based AIDI provides a transparent, reproducible, and comparable measure of disclosure coverage across firms and reporting years (Zhou and Bu, 2025), making it suitable for developing banking markets. Conceptually, it aligns with ESG and FinTech disclosure frameworks, which examine how transparency in emerging domains relates to firm performance (Eng *et al.*, 2021; Yasmine and Kooli, 2022; Aldboush and Ferdous, 2023; Amir *et al.*, 2025), but is now adapted to AI use in banking. To ensure reliability and validity in the content analysis, the study follows established principles for consistent coding and accurate interpretation (Milne and Adler, 1999), applying Krippendorff's (1980) procedures through a pilot test on 20 annual reports, a repeat test after one month, and an independent coder to evaluate inter-coder reliability.

3.3 Econometric model and analytical techniques

The study uses descriptive and inferential statistics to analyse the data. Descriptive statistics summarise bank performance through the mean, median, and standard deviation.

For inferential analysis, ROA, ROE, and CTI are modelled separately as dependent variables, with AIDI as the main independent variable and bank size, capital adequacy ratio, non-performing loan ratio, and net interest margin as controls. The analysis applies the two-step system GMM estimator in STATA 18, which is suitable for short panel data and helps address potential endogeneity, unobserved heterogeneity, autocorrelation, and simultaneity bias (Ullah *et al.*, 2018). Potential endogeneity may arise from reverse causality, where better-performing banks have greater incentives or resources to disclose AI activities, and from omitted bank-specific factors such as governance quality or digital capability. To address this, the study uses a two-step system GMM, which is suitable for dynamic panel settings and helps moderate simultaneity, unobserved heterogeneity, and performance persistence. The model also includes a lagged dependent variable and relevant bank-level controls (Jung and Kwon, 2007), while instrument validity is checked using the Arellano-Bond, Hansen, and Sargan tests. Where necessary, the instrument count is reduced using the collapse option to avoid instrument proliferation.

Before running the GMM estimations, diagnostic checks were performed to confirm robustness. Descriptive statistics (Table 1), the correlation matrix (Appendix B), and VIF values below 5 indicate no serious multicollinearity. GMM validity tests were then applied (Ullah *et al.*, 2018). The Arellano-Bond test shows AR(1) as expected and no AR(2), while the Hansen test supports instrument exogeneity. Although the Sargan test initially indicated instrument proliferation in the ROA model, it was corrected using the collapse option in xtabond2 (Khatib, 2024), after which both the Hansen and Sargan tests supported instrument validity. Difference GMM also confirmed robustness. Quantile regression (QR) was then used to examine whether the effect of AI disclosure varies across the 25th, 50th, and 75th percentiles of bank performance. The study employs 4 regression models as shown in Appendix A (Supplementary Materials).

4. Results

4.1 Descriptive statistics

Table 1 reports the descriptive statistics for the financial performance indicators and control variables. ROA shows a moderate spread, although some banks record negative returns. ROE varies more widely, indicating clear differences in equity performance across banks, consistent with Iskandar *et al.* (2021). CTI suggests efficient operations, though about one-quarter of banks show relatively high operating costs, similar to findings in Bangladesh and India (Mamun *et al.*, 2022; Kaur and Kaur, 2025). As a standardised Z-score, AIDI has a mean close to zero but varies considerably across banks and over time, indicating differences in AI disclosure intensity. Bank size also differs across the sample, while capital adequacy ratios indicate compliance with regulatory requirements. The non-performing loan ratio remains low, suggesting stable credit quality, whereas net interest margin varies, indicating differences in banks' ability to generate interest income.

Table 1. Descriptive statistics covering mean, minimum, maximum, standard deviation, and quartile distributions (25%, 50%, 75%)

Variable	Mean	Min	Max	SD	25%	50%	75%
ROA	0.82	−1.40	2.72	0.55	0.55	0.79	1.02
ROE	8.49	−14.36	24.26	5.18	5.17	8.80	11.49
CTI	0.54	0.26	1.33	0.20	0.43	0.49	0.63
AIDI	0.00	−2.35	2.62	1.00	−0.64	−0.08	0.58
BS	11.12	6.03	13.84	1.67	10.28	11.23	12.45
CA	0.28	0.11	1.50	0.42	0.18	0.20	0.26
NL	0.02	0.00	0.05	0.01	0.01	0.01	0.02
NI	2.15	−0.50	6.21	1.19	1.53	1.94	2.59

4.2 Correlation analysis and multicollinearity

[Appendix B \(Supplementary Materials\)](#) presents the correlation matrix. Most correlations are weak, except for the strong positive correlation between ROA and ROE (0.791), which is expected as both measure profitability. VIF values are all below 5, indicating that multicollinearity is not a concern and is unlikely to affect the regression results.

4.3 Two-step system GMM regression

[Table 2](#) reports the two-step system GMM results on the relationship between AI disclosure (AIDI) and bank performance, measured by ROA, ROE, and CTI. Only 128 bank-years were used because the inclusion of lagged dependent variables and instruments reduced the usable sample from 160 observations. The results show that AIDI has a significant positive effect on ROA (0.08) and ROE (0.74), but a significant negative effect on CTI (−0.03), indicating that greater AI disclosure is linked with higher profitability and better cost efficiency. The result supports signalling theory, which suggests that transparent disclosure of AI initiatives can improve investor confidence and market perceptions, thus improving financial performance ([Shiyyab et al., 2023](#)). The larger coefficient for ROE than ROA suggests a stronger effect on shareholder value, possibly through AI-related gains in customer segmentation, credit risk assessment, and investment strategies ([Mogaji and Nguyen, 2022](#)). The negative CTI coefficient is also consistent with earlier studies showing that AI automation can lower operating costs through process restructuring, fraud detection, and digital banking improvements ([Adewumi et al., 2024](#)). In short, the findings support proposed hypotheses and are consistent with signalling and stakeholder theory, as banks that disclose AI initiatives more transparently may attract investors, support regulatory trust, and improve financial stability ([Lee, 2020](#)). The results also align with [Bank Negara Malaysia \(2022\)](#), which notes that many financial service providers are already using AI and machine learning to improve decision-making and automate processes. Although the estimated effects are modest, they remain meaningful in a competitive and cost-sensitive banking environment, and may reflect gradual gains given the initial costs of AI investment ([Moharrak and Mogaji, 2024](#); [Moro-Visconti, 2024](#)).

Table 2. Two-step system GMM regression results on financial performance that are ROA, ROE and CTI

Variables	(1) ROA coef (t-stat)	(2) ROE coef (t-stat)	(3) CTI coef (t-stat)
L1.ROA	0.32 (2.15)**		
L1.ROE		0.75 (2.14)**	
L1.CTI			0.36 (1.99)*
AIDI	0.08 (2.04)**	0.74 (2.56)**	−0.03 (−2.70)**
BS	0.08 (1.75)*	0.55 (1.90)*	−0.02 (−2.00)**
CA	−0.08 (−1.60)	0.46 (2.05)**	0.03 (1.80)*
NL	−4.25 (−1.90)*	−18.22 (−2.00)**	−1.86 (−1.75)
NI	0.06 (1.50)	0.51 (2.10)**	−0.04 (−1.85)
Constant	−0.11 (−0.16)	−0.97 (−0.31)	0.61 (2.91)**
<i>Model fits</i>			
F-statistic [Prob > F]	86.32 (0.00)	441.71 (0.00)	285.98 (0.00)
Arellano-Bond test AR(1) [z, p value]	−1.64 (0.10)	−1.70 (0.09)	−2.08 (0.04)
Arellano-Bond test AR(2) [z, p value]	−0.03 (0.98)	0.83 (0.41)	−0.25 (0.80)
Sargan statistics - Chi-square [p value]	0.94 (0.33)	1.61 (0.21)	2.00 (0.16)
Hansen J-statistics - Chi-square [p value]	1.53 (0.22)	3.27 (0.071)	0.74 (0.39)
Number of observations	128	128	128
Number of instruments	6	8	8

Note(s): ****Indicates significant at 1% level

**Indicates significant at 5% level

*Indicates significant at 10% level

In addition to AIDI, several bank-specific factors influence profitability and cost efficiency. Bank size (BS) positively affects ROA and ROE, and lowers CTI, suggesting scale advantages and better cost efficiency in larger banks. Capital adequacy (CA) is positively related to ROE and weakly to CTI, implying that better-capitalised banks may face slightly higher operating costs. Non-performing loans (NL) reduce both ROA and ROE, confirming the negative effect of credit risk on returns. Net interest margin (NI) is significant only for ROE, indicating that wider interest spreads improve shareholder returns, though banks may still need alternative revenue sources.

4.4 Quantile regression

The GMM results show average effects, whereas quantile regression (QR) reveals differences across banks with varying performance levels. [Appendix C \(Supplementary Materials\)](#) shows that AIDI is insignificant for ROA and ROE across all quantiles, suggesting no consistent effect of AI disclosure on asset returns or shareholder returns, in line with [Shiyyab et al. \(2023\)](#). In contrast, AIDI is significantly negative for CTI at the 25th and 75th percentiles, indicating stronger efficiency gains among lower- and higher-cost banks. BS and NI remain significant across all ROE quantiles, while NL is positive and significant only at the upper ROE quantile. For CTI, NL is negative at all quantiles, but significant only at the lower and median levels, suggesting that banks with higher credit risk may apply tighter cost controls to preserve efficiency.

4.5 Robustness checks

Alternative GMM estimations (Difference GMM) produce consistent outcomes. AR(2) and Hansen results remain stable after instrument reduction using the collapse option ([Khatib, 2024](#)), confirming the validity of the instrument set and the robustness of findings.

5. Discussion

The findings show that AI disclosure is linked with higher profitability (ROA, ROE) and lower cost inefficiency (CTI). Transparent AI communication signals digital readiness and builds investor trust, consistent with signalling theory and stakeholder theory ([Shiyyab et al., 2023](#); [Lee, 2020](#)). It may also indicate deeper digital preparedness and support more resilient performance. The efficiency gains linked to AI disclosure are consistent with past studies on automation and intelligent systems, which highlight process improvement and decision accuracy as drivers of cost efficiency ([Adewumi et al., 2024](#); [Mogaji and Nguyen, 2022](#)). Yet, the quantile results show that these benefits are uneven, with stronger cost effects among banks that are already efficient or facing higher cost pressure. It suggests that AI disclosure does not generate value on its own but depends on internal capabilities, governance quality, and absorptive capacity. The pattern is similar to evidence from other emerging markets, where early adopters gained reputational and efficiency advantages, while slower banks faced adaptation pressure and regulatory scrutiny ([Mamun et al., 2022](#); [Moro-Visconti, 2024](#)). In Malaysia, the modest effect size likely reflects structural constraints, as local banks are still expanding AI infrastructure and integrating machine-learning tools into legacy systems ([Bank Negara Malaysia, 2022](#)). Thus, AI disclosure currently serves more as a legitimising mechanism, though it may become a stronger strategic differentiator as the ecosystem matures. These findings also relate to broader debates on AI governance and transparency in banking. As AI becomes more embedded in banking operations, attention increasingly turns to how it is disclosed, governed, and monitored. The positive relationship between AIDI and financial performance suggests that AI disclosure may serve not only as a reporting practice, but also as a governance signal that strengthens stakeholder confidence and market trust.

6. Implications

The findings offer both theoretical and practical implications for banking and regulation. By integrating signalling and stakeholder theories, the study explains how AI disclosure influences financial performance through signals of technological readiness and stakeholder assurance. It extends earlier work on financial and sustainability communication by highlighting technological transparency as a strategic driver of firm performance. It also adds to emerging research on AI in banking by showing that disclosure can serve both operational and reputational functions, supporting profitability, cost efficiency, and competitiveness. From a managerial and policy perspective, AI disclosure should be treated as a strategic communication practice rather than a compliance formality. More transparent AI reporting can improve investor confidence and market credibility, while standardised AI disclosure guidelines from regulators such as Bank Negara Malaysia could reduce information asymmetry, improve comparability, and help balance innovation with accountability.

7. Limitations and future research

Although the study produces new insights, several limitations remain. First, AIDI covers the extent of disclosure, but not its quality or tone, so future studies could use sentiment or narrative analysis as additional tests. Second, the focus on Malaysian commercial banks from 2019 to 2023 may limit generalisability, and larger samples from ASEAN or other emerging markets could reveal institutional differences in AI reporting. Third, the model includes key financial controls but excludes non-financial factors such as governance, digital capability, and ESG integration. Fourth, although the two-step system GMM and quantile regression address endogeneity and heterogeneity, the results remain correlational rather than causal. Finally, qualitative work, such as interviews with regulators or risk managers, could provide deeper insight into disclosure motivations, challenges, and benefits.

8. Conclusion

The study examined how AI disclosure impacts bank performance in Malaysia's developing financial sector. Based on signalling and stakeholder theories, it treats AI disclosure as a strategic communication tool and a disclosure-based proxy for banks' communicated AI engagement, rather than a direct measure of actual AI adoption. Using panel data from 32 banks between 2019 and 2023, and applying two-step GMM and quantile regression, the study developed the AIDI to measure transparency. The results show that AI disclosure is positively linked with profitability and operational efficiency, suggesting that credible technological reporting can boost investor confidence, cost discipline, and financial performance. Methodologically, the study contributes a replicable disclosure index and robust estimation approach, while practically highlighting AI disclosure as not only a compliance exercise but a potential source of resilience, trust, and competitive advantage in emerging markets.

Supplementary material

The supplementary material for this article can be found online.

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