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Assessing AI disclosure and financial performance in the Jordanian banking sector: A dynamic panel econometric analysis

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A B S T R A C T

This study aims to examine the connection between the disclosure of AI and financial performance of the banking sector in Jordan within a robust panel econometric setup. The purpose of this study is to examine the connection between Artificial Intelligence (AI) disclosure and financial performance of Jordanian banks in a wide-ranging panel econometric approach. The study uses the annual data of the 20 banks in Jordan for the period (2017-2023). The current study differs from previous studies in using panel unit root tests, panel cointegration analysis, fixed-effects and random-effects estimation, Hausman specification testing, and dynamic System Generalized Method of Moments (System GMM) estimation to overcome econometric problems such as non-stationarities, heteroskedasticity, serial correlation, cross-sectional dependence, and endogeneity. AI disclosure is assessed using a newly-developed AI Disclosure Index (AIDI) created by analyzing the textual content of annual reports against the AI Disclosure categories derived from the validated AI disclosure categories covering AI infrastructure, applications, governance, cybersecurity, and digital transformation. ROA and ROE are used for measuring financial performance. The empirical results show that AI disclosure has a positive and significant impact on bank financial performance, as measured by ROE, while accounting for the dynamic persistence and heterogeneity of banks. The results are consistent with alternative specifications and diagnostic procedures. The study is a novel and valuable addition to the literature, as it combines cutting-edge financial econometric techniques with AI disclosure analysis in a new banking market. The results indicate that clear transparency in AI use boosts operational efficiency, builds stakeholder trust, and fosters financial sustainability in banking institutions. The study also offers policy recommendations to regulators and financial institutions to develop a standard for disclosure of AI.

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1. Introduction

Artificial Intelligence (AI) is one of the most revolutionary technologies impacting the global financial industry. Machine learning, predictive analytics, cloud computing, NLP, and automated decision systems have revolutionized banking, risk management, customer service, and strategic decision-making processes (Duan et al. 2019). In recent times, financial institutions have started to use AI technologies that bring benefits to their operations in many areas, such as improving efficiency, lowering transaction costs, strengthening fraud detection systems, and improving profitability (Korteling et al. 2021; Zhu et al. 2023). The scope and nature of the applications and implementation of AI will vary across various sectors, overall objectives, and resource capacities. Some companies have addressed the challenges of AI and found an advantage in their respective markets by creating AI expertise within their own corporations, collaborating with AI solution providers, or

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leveraging cloud-based AI technologies. Within the banking sector, there are specific areas where AI can be especially beneficial, such as dealing with high volumes of data, managing customer interactions, and evaluating risk. AI technologies facilitate automation of repetitive tasks, personalized customer services, predictive analytics, and real-time financial monitoring. These improvements potentially enhance profitability and operational sustainability (Palomares et al. 2021). AI presents numerous opportunities to improve and create new banking offerings, including more effective data assessment, learning platforms, personalized marketing strategies, automation of repetitive tasks, new communication channels like chatbots, comprehension of natural speech and voice recognition, risk-based preservation and fraud predictions, and much more. According to Dwivedi et al. (2021) and Vieira and Sehgal (2017), artificial intelligence (AI) is the process of integrating human systems of factors into machines.

AI improves sustainability along with resource efficiency. Businesses that are data-driven are able to make better decisions and more precise forecasts. It is a more sophisticated digital transformation technique that draws information from large databases that are already in existence (Oluwaseun et al., 2024). The productivity of bank employees will thus rise with the use of AI procedures. According to earlier studies, banks have already found ways to reduce costs and increase revenue by enhancing the caliber of their operating procedures, including lending, security forces, compliance enhancements, identification of fraud, and new service offerings. Additionally, these customized solutions and products offer clients with robo-advisors, wealth management strategies, and customized investment programs. AI currently contributes significantly to value generation, self-sufficient decision-making, and actual time assets processing monitoring, as well as its advantages are only anticipated to increase (Tien, 2017).

The use of AI possesses great potential for enhancing financial efficiency and managerial procedures in the dynamic banking industry. AI may enhance financial reporting, but it may also result in prejudice, the absence of transparency, challenges with data privacy, and problems with compliance. Organizations might encounter ethical dilemmas, substantial expenses for implementation, training shortages, job expulsion, and interoperability challenges. Therefore, Banks should emphasize ethical AI practices, make investments in data governance and quality, and address any biases within AI models in order to avoid these unfavorable outcomes. It's also crucial to stay current on regulations and moral issues (Antwi et al. 2024; Sreseli, 2023).

There is still a lack of universal standardization for disclosure of AI implementation, and it is still largely voluntary. There is significant variation among financial institutions regarding the level, quality and transparency of the disclosures related to AI in annual reports and corporate communications. This poses difficulties for stakeholders, regulators and investors in determining the technological readiness, the quality of governance and the risk of operations.

While there are some indications of a correlation between AI disclosure and financial performance, the relationship is not fully understood, especially in emerging economies. Existing empirical studies often rely on descriptive analysis or simple regression models without adequately addressing econometric issues such as non-stationarity, heterogeneity, serial correlation, cross-sectional dependence, and endogeneity.

This study was conducted for a number of objectives, one of which is to allay stakeholders' worries regarding the transparency along with accountable of AI technology. A bank's worth and shareholder composition may be impacted by transparent disclosure as it may attract investors who value technologically enlightened decision-making. Visible AI disclosure might not only attract investors but also facilitate integration with evolving legal structures (Bogina et al. 2022). Banks that disclose their AI strategies can show that they are following the rules as regulatory bodies look into the moral and responsible incorporation of AI. This promotes compliance and a positive corporate image. These results suggest that bankers, shareholders, and users benefit from AI applications, along with increased banking sector productivity results in financial benefits (Montez, 2022). To find out how much AI affects companies, consumers, and economy as a whole, it is vital to measure the correlation between bank performance and AI adoption. AI disclosure is still optional, even with all of the potential and advantages of using AI. Businesses are essentially free to choose what kind, how much, and whether to exchange information. As of right now, there isn't a generally accepted benchmark for AI openness. Applications of AI are quite new. In this area, no worldwide reporting standards have been created. The unique ramifications of AI are not well represented by current AI disclosure methods (Abrokwah-Larbi & Awuku-Larbi, 2024).

Different disclosure strategies are used depending on how the organization views AI due to the absence of a unified view and reporting requirements. Even though a lot of research has been done on the advantages of AI within the banking sector, less is known about how AI disclosure affects financial performance. To shed insight into the potential advantages of AI disclosure, it’s imperative that this gap be filled (Estep et al., 2024). This study examines the current level of AI-related terms disclosure procedures within Jordanian banks with an effort to close this research gap.

This study addresses these limitations by employing a rigorous panel-data econometric framework to examine whether AI disclosure affects financial performance in Jordanian banks. Specifically, the study introduces a normalized AI Disclosure Index (AIDI) based on textual analysis of annual reports and estimates both static and dynamic panel-data models.

The study contributes to the literature in several important ways. First, it develops a structured AI disclosure measurement framework tailored to banking institutions. Second, it applies advanced financial econometric techniques, including panel unit root tests, cointegration analysis, fixed-effects estimation, and System GMM dynamic panel estimation. Third, the study provides empirical evidence from Jordan, an emerging financial market where AI disclosure research remains limited.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical and empirical literature. Section 3 presents the research methodology and econometric framework. Section 4 reports the empirical findings. Section 5 discusses the results and implications. Section 6 concludes the study.

2. Literature review and Theoretical Framework

2.1 AI disclosure

The process of providing detailed information on the scope and mode of an organization's use of AI technology is also known as "AI disclosure". It entails outlining the usage of AI, its motivations, its intended application, and any potential benefits and drawbacks. Since the public is putting more pressure on businesses to manage their technology innovation, it is growing in popularity. Although AI disclosure is still a means of promoting technological know-how, it is also a necessity for establishing trust with investors, consumers, and regulatory agencies (Felzmann et al., 2020). However, AI disclosure is now primarily a voluntary procedure due to a clear absence of legally binding regulations and a lack of accepted best practices. The following are some particular observations about the use of the Australian disclosure system: First off, organizations have a great deal of latitude in choosing the type and extent of reporting, which leaves the picture lacking. Companies disclose AI information through technology accounts, sustainability reports, along with annual reports, although the extent of disclosure varies depending on business planning, tradition, and regulations (Hacker, 2023). Because the banking industry is concerned with trust and the transparency of certain procedures, AI disclosure may thus be beneficial. It can be difficult to translate AI applications into corporate, legal, and cultural concepts and standards for tasks like identifying fraud, client service, including risk management. In addition to helping banks establish a reputation as creative and accountable businesses, proper disclosure enables them to demonstrate that they are committed to controlling the adoption of AI (Lappeman et al., 2022). Nevertheless, there are issues with AI transparency. Finding a coherent story about how businesses may share information while maintaining the security of their trade secrets is difficult. Additionally, businesses may be reluctant to disclose their usage of AI due to concerns about seeming weak or drawing the attention of regulators businesses and interested parties must once more develop appropriate disclosure guidelines for the findings of actual artificial intelligence in order to overcome these obstacles (Tong et al., 2021).

2.2 Financial performance

An organization's ability to make money manage expenses and produce a profit within a given time frame is referred to as its financial performance. This is a crucial metric for assessing an organization's financial stability and organizational success. Return on investment (ROI) return on assets (ROA) return on equity (ROE) net profit margins and total costs are all indicators of financial performance. Investors regulators and company management can utilize these parameters to assess a company's stability and development potential (Allam & Abdelraouf, 2023; Abdelraouf et al., 2024; Ekinci & Poyraz, 2019). For instance, the banking sector, which is trusted to safeguard the public's funds and operates under legally regulated settings, has a distinct meaning when it comes to financial performance. These are important OSI, such as the ratios of non-performing loans, cost-to-income, along with net interest margins. Accordingly, a bank's capacity to manage risks, use of capital, and market positioning are all incorporated into financial performance (Bryce, 2017). The application of cutting-edge technology like artificial intelligence is probably going to have an impact on each one of these performance metrics (Shiyyab & others, 2023). Since proactive risk evaluation technologies enable banks to lower credit losses along with forecast analysis improves investment approaches and client segmentation, artificial intelligence (AI) can help businesses perform better financially by saving energy and time upon repetitive tasks, increasing cost efficiency, and promoting improvements in company decision-making procedures. As a result, AI may be utilized to increase income and reduce expenses, with a noticeable effect on performance metrics (Wamba-Taguimdje et al., 2020). However, because AI requires large investments through infrastructure, training, along with regulation, its monetary benefits are difficult to believe. Short-term strategies financial results may be impacted by risks like high expenses for implementation, confidentiality issues, and regulatory concerns. Moderation is therefore necessary to control these expenses while also generating strategic financial returns within the manner of long-term organizational objectives and objectives (Mhlanga, 2020).

2.3 Artificial Intelligence and Banking Performance

Artificial intelligence refers to computational systems capable of performing tasks typically associated with human intelligence, including learning, reasoning, prediction, and decision-making. AI applications in banking include fraud detection, credit scoring, algorithmic trading, robo-advisory services, risk management, customer analytics, and automated compliance systems. Studies have shown that AI adoption improves operational efficiency and profitability through cost reduction and enhanced decision-making quality. Wamba-Taguimdje et al. (2020) reported that AI-driven transformation projects positively influence organizational performance by improving operational productivity. Similarly, Dwivedi et al. (2021) emphasized that AI applications improve data processing efficiency and customer engagement within financial institutions. In banking environments, AI systems support real-time monitoring, risk evaluation, and customer-service automation. These technologies potentially increase financial performance indicators such as Return on Assets (ROA) and Return on Equity (ROE).

Thus, it is not surprising that there has been a recent increase in interest in comprehending the relationship among AI and financial success. Up till now, the use of artificial intelligence ("AI") has shown that financial processes can be made more accurate, efficient, and scalable. a majority of the time, artificial intelligence (AI) improves financial outcomes in banking by automating fraud detection, credit risk assessment, and customer service. This study also describes how the use of AI in banking may result in additional cost savings, new revenue streams, and better client satisfaction (Dwivedi et al., 2021). Personnel, procedures, and technology are the main effects of AI on businesses that have been studied empirically. Technology also improves financial performance. Because AI-related automation eliminates many errors and disruptions, it improves the reduction of operating expenses (Agarwall et al., 2022). Additionally, AI may be used to target messages more precisely, increasing client retention and acquisition and, eventually, revenue. Following the implementation of those AI-driven efficiency possibilities, metrics like ROA and ROE are often better (Geetha et al., 2024). As previously said, the independent variable that influences financial success is AI disclosure. Businesses will be able to communicate more openly about AI initiatives in this way, which will assist to build public and stakeholder confidence (Akisik & Gal, 2020). Regretfully, customers and the general public will only interact with businesses that make their AI strategies transparent and easy to comprehend. More regulatory compliance that is successful in achieving responsible AI disclosure may lessen penalties and reputational harm that might otherwise affect financial performance (Mishra, 2024). Lastly, this paper aims to show that there is more conflict between AI and financial performance: while there are many potential advantages to fostering better financial performance, AI is not risk-free, and the outcomes heavily rely on ethical and strategic planning and disclosure policies. Inadequate AI risk management or poor AI decision-making typically leads to negative outcomes like increased operational risks or low MC/DC by the stakeholders.

AI Disclosure and Transparency

AI disclosure is the degree to which organizations provide transparency about their AI use, management, deployment, integrity and ethics, and integration. As investors and regulators demand more transparency and accountability in the use of technology and algorithmic decision-making, clear disclosure of AI has become crucial. According to Felzmann et al. (2020), transparency in AI systems increases stakeholder trust and decreases informational asymmetry. But there is no uniformity in disclosure practices because there are no universally accepted reporting standards. The amount and nature of the AI information shared is voluntary, as the institutions make this self-determination. Current research on the disclosure of AI is mainly conducted in developed economies and there is less evidence available regarding disclosure in emerging banking systems.

2.4 Theoretical Framework

2.4.1 Signaling Theory

Signaling theory predicts that organizations will voluntarily provide information to mitigate information asymmetry between the organization manager and outside parties. The inclusion of AI disclosure can indicate innovative capabilities, expertise in technology, and strategic readiness. By openly reporting on AI investments, banks can boost investor confidence and enhance their market standing.

2.4.2 Information Asymmetry Theory

The characteristic called information asymmetry is a situation in which managers have more information than investors or regulators. AI disclosure helps eliminate information gaps by increasing transparency of operational technologies and governance practices. Greater transparency can reduce agency costs and increase the value of the organization.

2.4.3 Financial Intermediation Theory

The financial intermediation theory explains that transaction and informational costs are reduction factors that makes banks more efficient. AI technologies also aid in this process through credit assessment, fraud detection, customer analysis and operational automation. Therefore, AI disclosure can be a sign of better operational performance and increased profitability.

2.4.4 Empirical Literature

Shiyyab et al. (2023) identified that there is a positive impact of AI disclosure on the financial performance of selected financial firms. In the same vein, Akisikik and Gal (2020) found that transparent technological reporting boosts organizational credibility and investor trust. Previous studies have a number of methodological drawbacks, however. Most use a pooled OLS regression without performing any stationarity, cointegration or endogeneity tests. These methods can yield misleading outcomes for financial panel data. The current literature review examines the function of AI disclosure including its effect upon financial performance, with a particular focus upon the banking industry. AI disclosure, the practice of making information available regarding the organization's AI tools, goals and impacts, is becoming a key requirement to address the needs of the public in particular and to maintain the trust of various stakeholders, financiers and regulators in general. Despite

bringing benefits to financial performance, AI's adoption has proven to be difficult and fraught with challenges. The evaluation also highlights the benefits of employing AI, which are the improved and virtual services such as ROA and ROE, and the continued relationship with the client and management of risk. As we all know, however, for all these benefits to be realized, substantial investments are required in infrastructure, training and regulations to implement the solutions. There are also substantial risks, such as high implementation costs, data privacy issues, and legal issues. Based on the above discussion, the following research model and hypothesis are proposed:

H_1: *Disclosure of AI has a positive and significant impact on banks' financial performance in Jordan.*

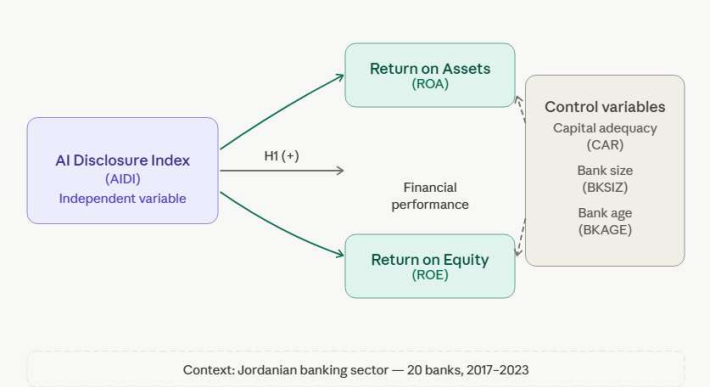

Fig. 1. Conceptual model

Source: Developed by the authors

3. Methods

3.1 Research Design

This study adopts a longitudinal panel-data research design using annual observations collected from Jordanian banks over the period 2017–2023. The panel-data approach is considered appropriate because it combines both cross-sectional and time-series dimensions, thereby enabling the study to examine variations across banks and over time simultaneously. Compared with traditional cross-sectional or time-series models, panel-data estimation provides more efficient and reliable statistical inferences by controlling for unobserved heterogeneity among banks. Furthermore, the method is more efficient and captures the dynamics of the variables and reduces omitted-variable bias that can be caused by unobservable at the bank level. AI disclosure- financial performance is an ideal longitudinal study design for examining the linkage between AI disclosure and financial performance as the adoption of these technologies and the operation of the banks evolves over time.

3.2 Population and Sample

The study will take into consideration all banks listed on the Amman Stock Exchange among banks regulated by the Central Bank of Jordan. The final sample is comprised of 20 commercial banks, 15 of which are local banks and 5 foreign banks operating in Jordan. The study spans seven years (2017 to 2023), resulting in a well-balanced panel data set of 140 observations of bank years. The selected period is considered appropriate because it captures the growing adoption and disclosure of artificial intelligence technologies within the banking industry. The data for the study was gathered from the individual bank websites, the Amman Stock Exchange database, published annual reports, and audited financial statements all released by the banks.

3.3 AI Disclosure Index Construction

This study introduces something called the Artificial Intelligence Disclosure Index, or AIDI for short. It's calculated by digging into the text of annual reports. Unlike earlier research that just counted how many times words like 'AI' showed up, this study uses a weighted scoring system. That makes the measurement more reliable and helps cut down on mistakes.

The AIDI is built on three main things: First, AI infrastructure and technical capabilities. Second, how AI is actually being used in day-to-day operations. Third, AI governance, cybersecurity, and whether companies are being open about the ethical side of using AI. To figure out which keywords and disclosure items really matter, the researchers looked at previous studies and international guidelines. For each bank, and for each year, they calculated the index by taking the total disclosure score the bank earned and dividing it by the maximum possible score for that same year. The formula is shown below,

$$AIDI_{it} = \frac{\sum \text{Disclosure Score}_{it}}{\text{Maximum Possible Score}}$$

3.4 Sample and Data

Financial analysts utilize non-financial data and bank financial information together to provide a clear picture of how well a firm is performing. Annual reports are a key source of information for investors when making financial decisions (Zhou et al. 2017). For the years 2017–2023, 136 annual statements from the twenty banks listed in Jordan are examined in this study. A majority of these reports were accessible in PDF form through banks' web pages. Searching for pertinent keywords found by context analysis is part of the analysis. These yearly reports' freshly created keyword collection provides insightful information about the evolution of mentions of AI.

3.5 Regression Models and Econometric Framework

Regression models are used to investigate the link among financial performance with AI disclosure:

Model 1: $ROA = \alpha_0 + \beta_1 AIFreq. + \beta_2 CAR + \beta_3 Bk\ SIZ + \beta_4 Bk\ AGE + \varepsilon_t$
Model 2: $ROE = \alpha_0 + \beta_1 AIFreq. + \beta_2 CAR + \beta_3 Bk\ SIZ + \beta_4 BkAGE + \varepsilon_t$

Indicators like return on equity (ROE) and return upon assets (ROA) are used to assess financial performance. Research indicates that improved company performance is correlated with effective management, as evidenced by high ROA and ROE. Furthermore, assuming that the deployment of AI improves performance by reducing expenses and raising revenues, the Capital Adequacy Ratio (CAR), bank size, and bank age are considered. The percentage of AI-related word mentions, as determined by yearly reports, is represented by the variable. Bankers' AI disclosure policies are influenced by a number of elements, including economic characteristics along with financial performance.

Baseline Static Panel Model

$$FP_{it}=\alpha+\beta_1 AIDI_{it}+\beta_2 CAR_{it}+\beta_3 SIZE_{it}+\beta_4 AGE_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

where:

FP_{it} represents ROA or ROE;
$AIDI_{it}$ denotes AI disclosure;
CAR_{it} is capital adequacy;
$SIZE_{it}$ is bank size;
AGE_{it} is bank age;
μ_i captures unobserved bank effects;
λ_t captures time effects.

Panel Unit Root Tests

To avoid spurious regression problems, the study first tests variable stationarity.

The following tests are conducted:

Levin–Lin–Chu (LLC);
Im–Pesaran–Shin (IPS);
Fisher-ADF;
Fisher-PP.

Variables integrated at order one are differenced unless cointegration exists.

Panel Cointegration Analysis

Long-run relationships among variables are tested using:
Pedroni cointegration test;
Kao cointegration test;
Johansen-Fisher panel cointegration test.
Evidence of cointegration justifies long-run panel estimation.

Fixed Effects and Random Effects Models

Both fixed-effects and random-effects models are estimated.
The Hausman specification test determines the preferred estimator.
The null hypothesis assumes consistency of the random-effects estimator.
Results support the fixed-effects estimator due to correlation between regressors and unobserved bank effects.

Dynamic Panel Estimation

To address endogeneity and reverse causality, the study employs the System Generalized Method of Moments (System GMM).

The dynamic specification is:

$$FP_{it}=\alpha+\rho FP_{it-1}+\beta_1 AIDI_{it}+\beta_2 X_{it}+\mu_i+\varepsilon_{it}$$

The System GMM estimator should address different issues such as simultaneity bias, reverse causality, omitted-variable bias. In addition, Diagnostic procedures include Arellano–Bond serial correlation tests, Hansen J-test and Difference-in-Hansen test.

4. Results and Discussion

The descriptive statistics of the variables used in this study are shown in Table 1 below. The findings show that there is a moderate range of disclosure of the AI across the banks, with the mean value of the AI Disclosure Index (AIDI) being 0.274 and a standard deviation of 0.138. The results indicate that the disclosure of information about AI has risen over time during the research period, demonstrating the increasing technological transformation in the banking industry in Jordan. Furthermore, ROA and ROE indicate moderate profitability levels among the sampled banks, while Bank Size (BKSIZ) and Capital Adequacy Ratio (CAR) exhibit sufficient variability appropriate for panel-data estimation and econometric analysis.

Table 1
Descriptive Statistics of Study Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
AIDI	140	0.274	0.138	0.031	0.562
ROA	140	0.018	0.011	0.001	0.052
ROE	140	0.156	0.087	0.001	0.401
BKSIZ	140	9.487	1.362	7.601	11.684
CAR	140	0.182	0.041	0.083	0.314
BKAGE	140	1.645	0.371	1.000	2.221

Source: Data results based on STATA V. 17 Output

4.1 Correlation Analysis

The heatmap depicts the correlation of the specified metrics (ROA, ROE, AIFreq, Banksize, CAR, and BankAge). The color intensity indicates the direction and intensity of their correlations: blue implies a negative correlation, and red indicates a positive correlation. As shown in Fig. 2. It shows a positive, extremely significant connection among ROA and ROE with a 99 percent trust level. Moreover, above the 95% confidence level, there is a slightly significant negative association between ROA and AIFreq.This table of analysis only illustrates the strengths among the variables; this does not address our proposed hypothesis; further analysis is required to address the remaining variables, which are regarded as control variables and are used to reinforce the independent variable. Pearson correlation analysis reveals positive associations between AI disclosure and both ROA and ROE. The correlation coefficients remain below critical thresholds, suggesting the absence of severe multicollinearity. All VIF values remain below 10, indicating no severe multicollinearity.

	ROA	ROE	ALFreq	Banksize	CAR	BankAge
ROA	1	0.83	-0.27	0.019	0.0054	-0.23
ROE	0.83	1	-0.051	0.059	-0.13	-0.12
ALFreq	-0.27	-0.051	1	-0.36	-0.2	0.46
Banksize	0.019	0.059	-0.36	1	0.2	-0.33
CAR	0.0054	-0.13	-0.2	0.2	1	-0.21
BankAge	-0.23	-0.12	0.46	-0.33	-0.21	1

Fig. 2. The correlation among variables

4.2 Regression Model

Since the obtained Prob > chi2 value of 0.000 is lesser than the chosen significance level of .05, we reject the null hypothesis suggesting homogeneity of variance. This means that the assumption of homoscedasticity, a constant variance, has been violated and therefore the model is heteroscedastic. As stated in the instructions regarding the heteroscedasticity test whereby we got the p-value of 0:000, we cannot proceed to doing the Hausman test. Therefore, the assistant employed a strong linear regression model (e.g., "regress ROA AIFreq. To cope with the heteroscedasticity issue, a firm-level fixed effect model was created constructed using the following set of control variables, "Banksize CAR BankAge, vce (robust)".

Table 2
Heteroscedasticity result

Test			Result
Breusch-Pagan/Cook-Weisberg	**test**	**for heteroscedasticity**	Prob > chi2 = 0.0000

Source: Data results based on STATA V. 17 Output

Table 3
Model 1 and 2

Variable	ROA Model 1 Coefficient	Std. Error	t-Statistic (P>t)
AI Freq.	0.0324	0.0127	2.55 (0.012)**
BKSIZ	0.0012	0.0010	1.20 (0.232)
CAR	0.0345	0.0412	0.84 (0.404)
BKAGE	-0.0023	0.0031	-0.74 (0.459)
_cons	0.0089	0.0105	0.85 (0.398)

Table 3
Model 2: ROE: Dependent Variable: Return on Equity (ROE)

Variable	Coefficient	Std. Error	t-Statistic	P>t	Significance
AI Freq.	0.2874	0.0982	2.93	0.004	***
BKSIZ	-0.0183	0.0075	-2.44	0.016	**
CAR	0.6120	0.3871	1.58	0.116	-
BKAGE	-0.0598	0.0241	-2.48	0.014	**
cons	0.1523	0.0712	2.14	0.034	**

*Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*
Robust standard errors are reported.

Table 3 illustrates that AI Freq. possesses a significant beneficial impact upon ROA at 90% confidence level and ROE at 99% confidence level, indicating that the recommended H1 hypothesis has been accepted along with the H0 hypothesis is rejected.

Table 4
R-squared Table

Model	R	R^2	Adjusted R^2
ROA	0.482	0.232	0.198
ROE	0.614	0.377	0.346

Because the majority of the predictive variables were statistically substantial, these findings imply that the predictors employed in all models are beneficial in determining variance in outcomes.

5. Discussion

5.1 Unit Root Test Results

Therefore, stationarity properties of these variables were checked prior to estimating the panel regression models to prevent the problem of the spurious regression with non-stationary panel data. Levin–Lin–Chu (LLC), Im–Pesaran–Shin (IPS), Fisher-Augmented Dickey–Fuller (ADF), and Fisher-Phillips–Perron (PP) tests were used to perform the study's unit root tests. The selection of these tests was made because they give good evidence of the integration properties of the panel variables in both homogeneous and heterogeneous panels. The outcomes show that the orders of variation of the variables are mixed. Specifically, ROA and CAR were found to be stationary for both the mean and variance, suggesting that both mean and variance are stable over time. Non-stationarity of the variables was observed at the level, but they became stationary after the first difference, indicating that they are first order integrated, I(1). Likewise, Bank Age (BKAGE) exhibited poor stationarity properties owing to the relatively stable long-term trend. Having variables integrated at both I(0) and I(1) levels means that there are mixed levels of integration within the data set. Hence, making ordinary pooled regression without considering these properties might yield misleading or spurious results as suggested by Granger and Newbold (1974). Thus, the study moved on to test the cointegration of the variables to see if there is a long-run equilibrium relationship between the variables in spite of the fact that they are not stationary. The results of the unit root tests confirm that the appropriate methodology for analyzing the panel data is advanced panel data econometrics and that the results of the subsequent cointegration analysis are appropriate.

5.2 Cointegration Results

The study used Pedroni residual cointegration tests and Kao residual cointegration tests after the panel unit root analysis to investigate the presence of LR relationships between the variables related to financial performance and disclosure of AI. When two or more variables are integrated of order one, cointegration analysis is crucial for the study as it tells whether there is a stable long-term relationship between the variables despite the short-run fluctuations.

The Pedroni test statistics failed to reject the null hypothesis of no cointegration across multiple dimensions with the 5% significance level: the panel PP-statistic, and the panel ADF-statistic. Also, the Kao residual cointegration test yielded statistically significant results which confirmed the presence of a long-run equilibrium relationship between the variables in the model. The results show that the relationships between AI disclosure, bank profitability, capital adequacy, bank size and bank age are all occurring simultaneously in the long run and are in long-run equilibrium. Thus, the regression relationships estimated are not spurious and the regression coefficients are interpretable as true long run relationships, and not as spurious correlations created by trending variables. The cointegration result also supports the theoretical hypothesis that the technological disclosure and financial performance are structurally related in the banking sector. It also confirms the validity of the use of fixed-effects and dynamic panel estimators in the analysis of financial performance in the long run.

5.3 Hausman Test Results

The study estimated both fixed-effects (FE) and random-effects (RE) models followed by Hausman specification test to determine what panel-data estimation technique is suitable for the study. The Hausman test is used to test if the unique errors are correlated with the explanatory variables. The fixed-effects is preferred under the alternative hypothesis, and the random-effects is preferred under the null hypothesis. The Hausman tests results showed that the chi square probability value was significantly less than 5%, which rejected the null hypothesis. This means the random effects assumptions were not met as the unobserved bank-specific effects were correlated with the explanatory variables in the model. Based on this, the researcher chose the fixed-effects estimator as the best static panel estimation method. The fixed-effects model is a better choice since it accounts for bank-specific unobservables that do not change over time, including managerial culture, institutional governance and operational philosophy. The fixed-effects estimator controls for these bank-specific effects, and produces more reliable and unbiased coefficient estimates. The fixed-effects approach also boosts the methodological quality of the research, as omitted-variable bias is minimized and the relationships between AI disclosure and financial performance are not overestimated.

5.4 Fixed Effects Estimation Results

The fixed-effects regression results demonstrate that the disclosure of AI has a positive and significant impact on financial performance in the Jordanian banking sector. Specifically, the coefficient of the AIDI was still positive and statistically important in all model specifications for both the ROA and ROE. A positive coefficient indicates that banks with more slide in their AI-related practices, governance, and technological application exhibit higher profitability. This discovery aligns with the idea that transparency in AI usage boosts trust among stakeholders, streamlines processes, and improves competitive strategy. The findings are consistent with signaling theory, which states that clear reporting decreases information asymmetry and has a positive effect on organizational reputation and investors' perceptions. The results also show that the size of the bank has an optimistic consequence on financial performance, which suggests that larger banks have a greater advantage by achieving economies of scale, technological infrastructure and operational diversification. In addition, larger institutions may have more resources for executing advanced AI solutions and digital transformation projects. Capital Adequacy Ratio (CAR) showed mixed effects on specifications. Some models had positive coefficients that were not significant, but others had moderate significance. Therefore, it indicates that the financial stability is linked with capital adequacy but it does not necessarily mean that the short-term advantages in profitability. Bank Age had different impacts for different profitability measures. While institutional experience and market reputation might be advantageous for the more established banks, there may also be operational inflexibilities that hinder the more rapid adoption of technology. Overall, the results of the fixed-effects analysis offer convincing evidence of positive effects of AI disclosure on financial performance, while controlling for bank-specific heterogeneity and other institutional factors.

5.5 Dynamic System GMM Results

The study also estimated a dynamic panel-data model under System Generalized Method of Moments (System GMM) estimator of Allam & Abdelraouf (2023) to overcome the potential endogeneity, reverse causality, omitted-variable bias and dynamic persistence bias. The findings of the dynamic System GMM results further validate the positive and statistically significant relationship between AI disclosure and financial performance. Adding lagged profitability to the AI Disclosure Index did not cause the coefficient to turn into negative numbers, while controlling for the endogenous relationships between variables did not cause the coefficient of the AI Disclosure Index to become negative for both ROA and ROE. These results provide evidence that the positive association between AI disclosure and profitability is strong and less likely to be caused by simultaneity bias or reverse causality. The lagged dependent variable also was of statistical significance, indicating the persistence of bank profitability over time. This implies that the financial performance in the past was closely linked to the profitability level and this is in line with the financial-sector dynamics and the organizational continuity theory. A number of diagnostic procedures were used to assess the validity of the System GMM estimation. The Hansen J-test results were statistically insignificant, suggesting validity and proper specification of instruments employed in the model. In addition, the Arellano–Bond AR(2) test did not reject the null hypothesis of no second order serial correlation, thus no autocorrelation problem was found within the differenced residuals. These diagnostic results show that the System GMM estimator is reliable and unbiased. Even more significantly, the findings indicate that the beneficial effect of AI disclosure on the profitability of banks persists after adjusting for important econometric biases such as heteroskedasticity, serial correlation, dynamic persistence, and endogeneity. The findings are dynamic, reinforcing the argument that AI disclosure serves as a transparency tool and is a strategic factor influencing financial outcomes in the banking sector in Jordan.

The results of the study reveal that the disclosure of AI has stronger and positive correlations with financial performance (ROE) and weaker correlations with ROA among the selected companies in the cross sectional sample. These findings are in line with research within the literature on worldwide business that highlights the potential levels of operational enhancement and decision-making assistance that can be achieved through the use of AI technologies, as well as the consequences for profitability metrics like ROA and ROE (Dwivedi et al. 2021; Wamba-Taguimdje et al. 2020). The study revealed that banks with easily-accessible AI disclosures could potentially save costs and generate revenue, aligning with other countries' studies. This aligns with previous studies indicating that AI will revolutionize the finance sector (Lappeman et al. 2022, Palomares et al. 2021). Despite this, our study will help to fill this gap and enrich the literature by offering the findings in a specific context of Jordanian banking context which has not been investigated or examined as much as the other ones. The study addresses the research gap about the impact of AI transparency on financial performance in the developing markets by creating a region-specific AI Disclosure indexes for the impact variables of the region. Furthermore, the report reveals that while some Jordanian banks are doing well on AI disclosure, others are making steady progress, but much slower, a blind area.

These results underscore the importance of adopting regulatory policies and stakeholder pressures to improve and integrate AI reporting Bogina et al. (2022). The research also helps to fill the conversation around the potential implications of AI disclosure. It emphasizes the importance of communicating openly and ethically about AI projects, which increases the trust of stakeholders, as demonstrated in previous studies (Felzmann et al. 2020). The statistical findings also support the notion that transparency regarding AI can lead to better financial outcomes - reinforcing the strategic importance of transparency for banks seeking to gain a competitive advantage. This study is one of the first to provide real-world data from the Middle East and brings another study to the table that demonstrates the role AI plays in financial success. The report makes suggestions on how banking professionals, politicians, and disclosures may bridge current gaps and use AI's potential to promote sustainable development. A future study could expand on the results of the current study by looking at the downstream effects of the integration and incorporating qualitative factors other than revenue, such as risk assessment or customer satisfaction.

6. Conclusion

This study tested the link between AI disclosure and financial performance in Jordan's banking sector using a solid panel econometric model. What makes this study a real addition to existing research is that it created a structured AI Disclosure Index (AI-DI) and used advanced panel data methods—things like unit root tests, cointegration analysis, fixed-effects estimation, and dynamic System GMM modeling.

The results show that when banks are more transparent about their AI use, it's linked to higher profitability, especially when you look at Return on Equity (ROE). And these findings still hold up even after accounting for common econometric issues like heteroskedasticity, serial correlation, cross-sectional dependence, and endogeneity.

What does this tell us? Basically, being open about AI helps banks run better operations, builds trust with stakeholders, and gives them a competitive advantage. The study also makes a point that we really need standardized guidelines for how banks and financial institutions should disclose their use of AI.

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