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Non-Performing Loans, Bank Performance, and Financial Stability:

The Moderator Effect of Digitalization

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Abstract

Purpose- This paper examines how digitalization moderates the relationship between non-performing loans (NPLs), bank performance, and financial stability in the banking sector.

Design/methodology/approach - The study applies panel data regression techniques to banks operating in 18 MENA countries over the period 2000–2023. Bank performance is measured using return on assets (ROA) and return on equity (ROE), while financial stability is proxied by the Z-score. Digitalization indicators are included both directly and through interaction terms with NPLs to capture their moderating effect. Several robustness tests are conducted to validate the results.

Findings - Results show that NPLs negatively affect bank performance and financial stability, highlighting the destabilizing impact of deteriorating credit portfolios. Digitalization exerts a direct positive effect by improving credit monitoring, information processing, and operational efficiency. Interaction results indicate that higher digitalization levels significantly reduce the negative effect of NPLs on profitability and resilience. Managerially, banks investing in advanced credit-risk analytics, automated loan monitoring, and digital customer screening tools are better able to mitigate NPL-related losses, detect early loan deterioration, and improve recovery strategies. These findings contribute to Decision Sciences by demonstrating how technological adoption enhances risk prediction, managerial decision-making, and strategic resource allocation.

Originality/value - This study offers new empirical evidence on the moderating role of digitalization in the NPL–performance–financial stability nexus through one of the first long-term panel analyses of the MENA banking sector spanning more than two decades. It extends existing literature by quantifying the impact of technological adoption on credit risk–performance dynamics in emerging markets.

Practical implications - The findings provide actionable insights for managers and policymakers. Banks should prioritize investments in (1) AI and machine learning for predictive credit scoring and early-warning systems, (2) integrated digital loan management platforms for improved monitoring and recovery, and (3) digital customer data infrastructures to reduce information asymmetry. Regulators can support digital transformation through regulatory sandboxes and fintech partnerships to strengthen financial stability. Overall, targeted digitalization strategies can reduce NPL accumulation, enhance efficiency, and improve long-term resilience.

Keywords: Non-performing loans; bank performance; financial stability; digitalization; moderating effect

JEL Classifications : G21 ; G32 ; O33 ; C23

1 Introduction

Digitalization has become a key strategic lever in the banking sector, transforming management methods, customer interactions, and service delivery. It not only offers opportunities to improve operational efficiency and reduce costs but also plays a crucial role in managing risks associated with non-performing loans (NPLs). In the Middle East and North Africa (MENA) countries, where NPLs pose a major challenge to financial stability and bank profitability, digitalization could potentially mitigate these negative impacts.

The digital transformation has revolutionized the global financial sector, providing banking institutions with new opportunities while confronting them with unprecedented challenges. In the MENA region, this shift towards digitalization is of critical importance, particularly when viewed through the lens of bank performance and its relationship with NPLs.

Ahmed and Sur (2023), highlight the significant impact of digitalization on banking practices in MENA countries. Their research demonstrated how the adoption of new technologies has helped improve banks' operational efficiency, optimise customer data management, and increase financial inclusion. However, despite these benefits, challenges remain, especially in terms of risk management related to non-performing loans.

Similarly, Khan et al. (2024) examined the correlation between digitalization and NPLs in the MENA region. Their study revealed that while digitalization can enhance transparency in banking operations and improve borrower monitoring, it may also introduce new cybersecurity and fraud risks, potentially affecting banks' asset quality and increasing NPL levels.

Unlike previous studies, which mainly focused on the direct effects of digitalization or risk management related to non-performing loans, this study takes a unique integrated approach by examining the moderating role of digitalization on the relationship between bank performance and non-performing loans in MENA countries. By utilizing recent data and advanced econometric models, this study offers fresh empirical evidence on how digitalization can reduce risks, improve profitability, and enhance financial stability within a specific regional context characterized by structural and technological challenges.

This study contributes to Decision Sciences by offering analytical tools that enable bank managers and policymakers to optimise digitalization strategies in order to improve risk management related to non-performing loans and enhance overall financial institution performance within a complex and uncertain environment.

In this complex context, it is essential to thoroughly explore how digitalization acts as a moderating factor between bank performance and non-performing loans in MENA countries. Current research provides valuable insights into the mechanisms through which technology influences risk management and profitability of financial institutions in the region, and how these factors interact to impact overall financial stability.

By analysing these complex interactions and building on lessons learned from recent studies, this paper aims to make a meaningful contribution to ongoing discussions on the challenges and opportunities associated with digitalization, financial performance, and bank stability in MENA countries.

To achieve this objective, the remainder of this paper is organised as follows: Section 2 presents the literature review and hypothesis development. Section 3 addresses methodological aspects, including the sample and models. Section 4 presents the main empirical results and discussion. Finally, conclusions are provided in Section 5.

2 Literature Review and Hypothesis Development

2.1 Relationship between Non-Performing Loans and Bank Performance

Non-performing loans (NPLs) play a crucial role in assessing the financial health of banking institutions, particularly in the MENA region. Recent research by Albaity et al. (2023) highlights the deleterious effects of NPLs on different aspects of bank performance, providing in-depth insights into the challenges faced by these institutions.

Marouli et al. (2023) highlight the destabilizing effect of NPLs on banks in Greece. The results showed that banks facing high levels of NPLs experience a decrease in their profitability and solvency, which limits their ability to provide loans and stimulate economic growth.

Ayinuola and Gumel (2023) highlight that the increase in non-performing loans in Nigerian banks is putting significant pressure on their profitability and solvency. This research revealed that banks with high levels of NPLs struggle to maintain stable profit margins and meet capital requirements, thereby compromising their ability to sustain growth and manage financial risks. In the same research context, Gupta and Bansal (2024) examined the NPL management strategies adopted by banks in the region. The findings highlighted the critical importance of information transparency, diligence in credit provision, and effective recovery mechanisms to mitigate the impact of NPLs on bank performance and maintain stakeholder confidence. Khan et al. (2020) highlight the impact of NPLs on investor confidence and the financial stability of banks in the MENA region. The results showed that the presence of high NPLs can lead to increased volatility in bank stocks, significant outflows, and a deterioration in investors' perceptions of the financial strength of institutions, thereby threatening their long-term stability. Similarly, Chen et al. (2023) found that the increase in non-performing loans in banks in the region has a significant impact on investor confidence and financial stability. Asian banks with high levels of NPLs have faced challenges in maintaining their attractiveness to investors, which has hampered their ability to raise affordable funding.

From a more practical perspective, Boussaada et al. (2023) examine the NPL management strategies adopted by European banks. This research identified the importance of putting in place adequate provisioning policies, effective recovery processes, and rigorous monitoring mechanisms to reduce the impact of NPLs on the overall performance of banks and strengthen their resilience to economic shocks.

By consolidating the findings of this research and integrating them into the current understanding of the relationship between non-performing loans and bank performance in MENA countries, it becomes evident that proactive credit risk management and the implementation of effective asset management strategies are essential to ensure the sustainability and prosperity of financial institutions in a constantly changing economic environment. Based on previous studies, we formulate the following hypothesis:

Hypothesis 1: Non-performing loans have a significant and negative impact on the financial performance of banks in MENA countries.

2.2 Impact of Non-Performing Loans on Banks' Financial Stability

Non-performing loans (NPLs) have been identified as a critical factor influencing the stability of financial institutions in various contexts. Recent studies conducted in different regions shed light on the relationship between NPLs and banks' financial stability.

Garcia and Abreu (2024) found that increasing NPLs in banks directly impacts their solvency. High levels of NPLs can compromise banks' ability to meet capital requirements, potentially affecting their resilience to economic downturns and overall financial stability.

Ok et al. (2019) indicated that NPLs have a negative impact on banks' profitability in the region. Costs associated with managing NPLs, such as provisions and impairments, can reduce banks' profit margins, posing challenges to revenue generation and long-term financial stability.

Lim et al. (2023) highlighted the systemic risks associated with non-performing loans to overall financial stability. High levels of NPLs can lead to risk contagion across institutions, potentially destabilizing the banking sector and requiring regulatory intervention to prevent a financial crisis. Based on previous studies, we hypothesize:

Hypothesis 2: Non-performing loans have a negative impact on banks' financial stability in MENA countries.

2.3 Relationship between digitalization and banking performance

Digitalization has transformed the global banking landscape, providing unique opportunities for financial institutions to enhance their performance, operational efficiency, and competitiveness. A recent literature review highlights the positive impact of digitalization on banking performance in various regional contexts. Similarly, digitalization has emerged as a key driver of banking performance, offering opportunities for operational efficiency, improved customer experience, and new business models.

Recent research, such as that conducted by Saidi et al. (2024), has shown that banks investing in digital transformation can increase productivity, reduce costs, and strengthen their market competitiveness.

In the same vein, Grassi et al. (2022) examined the impact of FinTech adoption on the performance of traditional banks. The results showed that banks successfully integrating innovative technological solutions into their operations can improve efficiency, reduce transaction costs, and provide a more personalized customer experience, thereby strengthening their market position.

Similarly, Lee, C. C. (2023) explored how the digital transformation of regional banks has contributed to improving financial inclusion and expanding access to Asian banking services. Digitalization has enabled institutions to reach new segments of the population, offer financial products tailored to local needs, and strengthen the stability of the financial system in the region.

An in-depth analysis by Restrepo-Morales et al. (2024) examined the effects of technological innovation on bank profitability in an increasingly digital environment. The results highlighted that financial institutions investing in cutting-edge technologies, such as artificial intelligence and blockchain, can improve operational efficiency, reduce risks, and increase long-term profitability. Based on previous studies, we formulate the following hypothesis:

Hypothesis 3: Digitalization is positively associated with banking performance in the MENA region.

2.4 Digitalization and Financial Stability

Maintaining the stability of the banking sector is essential not only for ensuring price stability, a primary goal of central bank monetary policies, but also for fostering economic growth. Banking sector stability refers to a state where financial institutions are robust enough to withstand economic shocks and effectively carry out financial intermediation. This issue is particularly relevant in various emerging markets across the globe, where the financial landscape is rapidly evolving.

In terms of banking stability, academic research suggests that digitalization can play a key role in enhancing financial stability by promoting financial inclusion, increasing transparency, and enabling more effective risk management. Studies, such as those conducted by researchers like Zaman et al. (2023), have shown that digital financial inclusion can improve stability by expanding access to banking services for underserved populations, reducing financing constraints for small businesses, and improving overall risk assessment capabilities. Moreover, a broader network of digital banking services and increased access to digital financial tools per capita are likely to contribute to enhanced bank stability.

However, a major concern is the need for traditional banks to effectively address operational, regulatory, and economic challenges when integrating fintech solutions. The disruptive impact on the traditional banking models in these regions can pose risks to systemic stability, consumer protection, and market competition. While traditional banks in emerging markets have the opportunity to innovate through competition with fintech firms, experts such as Lee, J.W. (2023) argue that a cautious approach to collaboration with these innovative entities is necessary. This caution stems from the regulatory constraints that traditional banks face, limiting their agility compared to fintech firms.

Currently, there is a lack of a formal regulatory framework governing the integration of digitalization in partnerships with traditional banks in various emerging markets. This absence raises concerns about systemic risk implications, a point highlighted by researchers such as Gupta and Bansal (2024). International organizations like the World Bank recognize the importance of monitoring fintech developments to identify risks and adapt regulatory frameworks accordingly (Ok et al., 2019). The focus should not be on whether partnerships will occur, but on when and how they will take shape. While the absence of partnerships may hinder the progress of traditional banks, scholars emphasize the need for cautious collaboration to ensure financial stability in emerging markets (Lim et al., 2023). Based on previous studies, we formulate the following hypothesis:

Hypothesis 4: Digitalization significantly impacts the financial stability of banks.

2.5 The moderator effect of digitalization

Recent literature emphasizes the growing importance of digitalization in the banking sector. Studies such as Kou et al. (2024) highlight that the adoption of digital technologies can strengthen banks' resilience to financial shocks by improving credit risk management. Similarly, research by Chen et al. (2023) showed that digitalized banks are more efficient in monitoring and recovering loans, thereby helping to reduce the non-performing loan rate. Regarding the financial stability of banks, studies such as Lee et al. (2023) highlight that digitalization can enhance transparency, reduce operational costs, and improve risk management, which are crucial for maintaining financial stability. Furthermore, the work of Zaman et al. (2023) highlights that digitalization can increase the resilience of banks by allowing them to adapt more quickly to market changes, thereby strengthening their position in volatile economic environments. Based on previous studies, we formulate the following hypothesis:

Hypothesis H5: Investment in digitalization by banks could reduce the negative impact of non-performing loans on their performance and strengthen their financial stability.

3 Methodology

In this section, we will first discuss the sample selection and data sources used in the empirical study. Secondly, we will present the explanatory and explanatory variables, as well as the econometric methodology employed.

Our study focuses on analyzing the financial performance stability of banks in MENA countries using a panel data regression model. This approach offers several advantages, particularly in terms of considering both the cross-sectional and time dimensions of the data. Furthermore, utilizing panel data leads to more robust and reliable results compared to time series analysis.

In this study, we utilize panel data, which combines observations on multiple units (countries, firms, etc.) over various time periods. This type of data enables us to consider both the temporal dimension and individual heterogeneity. Two main estimation methods are under consideration: the fixed effects (FE) model and the random effects (RE) model. The fixed effects model controls for unobserved, unit-specific characteristics that are assumed to be correlated with the explanatory variables. In contrast, the random effects model assumes that these specific effects are random and uncorrelated with the explanatory variables. To determine the appropriate approach, we conduct the Hausman (1978) test and the Altman (1968) test. If the test yields significance, the fixed effects model is preferred; otherwise, the random effects model is considered more efficient. The results of this estimation will be presented in Tables 5, 6, and 7, respectively.

3.1 Model specifications and statistical method

The econometric models are expressed as follows:

Direct effect models

$$ROA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (1)$$

$$ROE_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (2)$$

$$Z - Score_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (3)$$

$$ROA_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (4)$$

$$ROE_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (5)$$

$$Z - Score_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}. \quad (6)$$

In Equations 1 to 6, the dependent variables include ROA_{it} and ROE_{it}, representing the return on assets and return on equity of bank *i* in year *t*, respectively, as well as the $Z - Score_{it}$, which measures the financial stability of bank *i* in year *t*. The model also incorporates key explanatory variables, including NPL_{it}, the non-performing loans of bank *i* at year *t*; DIG_{it}, capturing the degree of digitalization within the bank; LIQ_{it}, representing the bank's liquidity level; and $CRINFOR_{it}$, indicating the extent of credit information sharing. Control variables account for bank-specific and macroeconomic conditions, such as $BASSET_{it}$, the size of bank *i*; BIR_{it}, the interest rate faced by the bank; INF_{it}, the inflation rate of country *i*; and EG_{it}, the economic growth rate of country *i* in year *t*. All variables are measured on an annual basis over the sample period.

To study the moderating effect of digitalization between non-performing loans and bank performance and financial stability. The econometric models are expressed as follows:

Moderator effect models

$$ROA_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 NPL_{it} + \beta_3 DIG_{it} * NPL_{it} + \beta_2 CRINFOR_{it} + \beta_3 LIQ_{it} + \beta_4 BIR_{it} + \beta_5 BASSET_{it} + \beta_6 INF_{it} + \beta_7 EG_{it} + \varepsilon_{it}, \quad (7)$$

$$ROE_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 NPL_{it} + \beta_3 DIG_{it} * NPL_{it} + \beta_4 CRINFOR_{it} + \beta_5 LIQ_{it} + \beta_6 BIR_{it} + \beta_7 BASSET_{it} + \beta_8 INF_{it} + \beta_9 EG_{it} + \varepsilon_{it}, \quad (8)$$

$$Z - Score_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 NPL_{it} + \beta_3 DIG_{it} * NPL_{it} + \beta_4 CRINFOR_{it} + \beta_5 LIQ_{it} + \beta_6 BIR_{it} + \beta_7 BASSET_{it} + \beta_8 INF_{it} + \beta_9 EG_{it} + \varepsilon_{it}. \quad (9)$$

3.2 Definitions and measures of variables

Analysis of the diversity of work that has dealt with banking performance and its measures reveals that three performance measures are frequently used: return on assets (ROA), return on equity (ROE), and the net interest margin (NIM). In the context of our study, we only use the first two measures (ROA and ROE). This choice is justified by the fact that these indicators constitute the most useful measures of bank profitability over time because assets have a direct effect on income and expenditure (Kosmidou et al., 2007; Van Horen, 2007). Likewise, this ratio reflects the bank's ability to generate income from its assets. Finally, return on assets and return on capital have become the most common measures of bank profitability in the literature (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011; Olson & Zoubi, 2011).

The Z-score is a statistical measure used to assess the financial stability of banks, indicating the distance in standard deviations of a bank from insolvency. It is calculated from the return on assets (ROA), the ratio of capital to assets, and ROA volatility. A high Z-score suggests greater stability. Studies such as Altman's (1968) on bankruptcy prediction, as well as the work of Boyd and Runkle (1993) on bank performance, explore the effectiveness of this measure. In addition, Laeven and Levine (2009) analyze how bank governance and regulation influence risk, using the Z-score for their assessments. This research provides insights essential to the risk management and resilience of financial institutions.

Digitalization: Innovations Index (0–100): The Innovations Index is a composite indicator measuring the level of digital and technological innovation in the banking and financial sector. It is sourced from the World Bank's Global Innovation Index (GII) database, which provides standardized cross-country measures of innovation performance. The index is constructed by aggregating several sub-dimensions, including ICT infrastructure, digital adoption, research and development intensity, knowledge creation, and technology diffusion. Each sub-component is normalized and combined using the weighting scheme defined by the World Bank methodology, and the final score is rescaled to range from 0 to 100, with higher values indicating a higher degree of innovation and digital capability. This index has been widely used in the empirical literature to proxy digitalization and innovation capacity in financial and economic studies, ensuring cross-country comparability and methodological consistency.

Table 1 below groups together the explanatory variables developed in the literature review, as well as the measures used for each factor retained in the econometric model.

Table 1: Summary of study variables

Variable name	**Notation**	**Measurement of variables**
Financial performance	ROA ROE	Bank return on assets, in percent: Net income / total assets Bank return on equity, in percent: Net income / Equity
Financial stability	Z-score	$Z - score = (ROA + Equity/Asset) / \sigma(ROA)$
Non-Performing Loans	NPL	non-performing loans / total loans
Digitalization	DIG	Digitalization = Innovations index (0-100)
Liquidity	LIQ	Liquid assets / total assets
Credit information	CRINFOR	Credit information sharing index, Binary variable: 1 if index ≥ 5, 0 otherwise
Bank assets	BASSET	Bank assets, percent of GDP
Interest rate	BIR	Real interest rate of the bank
Inflation	INF	Inflation rate of countries: percent change in the Consumer Price Index
Economic growth	EG	Economic growth forecast

3.3 DATA

This study uses annual data from 18 MENA countries over a 24-year period (2000–2023), totaling 432 observations. The dataset was gathered from various sources such as TheGlobalEconomy.com, DataStream, and the World Bank. It includes financial metrics, macroeconomic variables, and bank-level information essential for the analysis.

3.3.1 Descriptive statistics

Table 2: Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
ROA	1.6233	1.2134	-2.5900	13.0900
ROE	14.4913	9.3730	-66.4700	77.7100
Zscore	22.7347	12.6333	0.0200	66.6300
NPL	8.1006	6.0045	1.0800	23.8200
DIG	31.2026	6.8635	13.6000	47.7000
EG	3.5003	8.0736	-50.3400	86.8300
INF	7.5728	19.3620	-10.2800	224.4400
BASSET	65.6690	40.2375	3.4500	235.3600
BIR	3.0390	1.4867	0.1700	20.5000
LIQ	42.4749	24.1140	9.7800	130.4200
CRINFOR	0.4925	0.5175	0.0000	1.0000

Note: All variables are measured on an **annual basis**. **ROA** represents the return on assets of bank *i* in year *t*, while **ROE** measures the return on equity of bank *i* in year *t*. **Z-score** captures the financial stability of bank *i* at year *t*, and **NPL** denotes non-performing loans. The degree of digitalization of bank *i* is represented by **DIG,** while **LIQ** indicates the bank's liquidity level. Bank-specific and macroeconomic control variables include $\mathbf{BASSET_{it}}$, the size of bank *i*; $\mathbf{BIR_{it}}$, the bank's interest rate; **INF**, the inflation rate of country *i*; and **EG**, the economic growth rate of country *i* in year *t*. **CRINFOR** is a binary variable indicating high (≥5) versus low (≤4) credit information sharing.

The descriptive statistics in Table 2 provide key insights into various financial variables. The average return on assets (ROA) is 1.62%, indicating the return on assets, while the average return on equity (ROE) is 14.49%, illustrating the return on equity. The average Z-score of 22.7347 suggests moderate financial stability. Economic growth (EG) averages at 3.5000, reflecting moderate earnings growth. The average inflation rate (INF) is 7.57% with high variability. The average asset size (BASSET) is 65.6690, and the non-performing loan (NPL) rate averages at 8.1006. The average base interest rate (BIR) is 3.04%. The average liquidity (LIQ) is 42.4749, and the average credit information level (CRINFOR) is 0.4925. Finally, the average level of digitalization (DIG) is 31.2000. The CRINFOR index, originally measured on a 0–8 ordinal scale, has been transformed into a binary variable, CRINFOR_high, to distinguish between low and high levels of credit information sharing. Specifically, values ≥5 are coded as 1, representing high information sharing, while values ≤4 are coded as 0, representing low information sharing. This transformation ensures that the ordinal nature of the index is respected in the econometric analysis. Descriptive statistics indicate that approximately half of the observations fall into each category, providing a balanced sample for analysis.

These statistics offer a comprehensive overview of the financial performance and characteristics examined, highlighting trends and potential risk levels in the analyzed dataset.

3.3.2 Correlation Matrix

The correlation matrix provides an overview of the linear relationships between different financial variables (see Table 3).

Table 3: Correlation Matrix

	EG	INF	BASSET	NPL	BIR	LIQ	CRINFOR	DIG
EG	1.0000							
INF	0.1998**	1.0000						
BASSET	-0.1342*	-0.3362***	1.0000					
NPL	0.0696	0.4027***	-0.2966***	1.0000				
BIR	0.0526	0.3599***	-0.4614***	0.4306***	1.0000			
LIQ	-0.1906**	0.1022	0.2541***	0.4277***	0.0178	1.0000		
CRINFOR	-0.0230	-0.2866***	0.3378***	-0.4902***	-0.5151***	-0.4165***	1.0000	
DIG	0.1171	-0.3462***	0.1803**	-0.4346***	-0.5743***	-0.4644***	0.5118***	1.0000

Note: The table reports the correlation coefficients among all variables used in the analysis. **EG** represents the economic growth rate of country *i* in year *t*, **INF** denotes the inflation rate, and **BASSET** measures the total assets of bank *i*. **NPL** is the ratio of non-performing loans, **BIR** denotes the bank interest rate, and **LIQ** captures the liquidity level of bank *i*. **CRINFOR** is a binary variable indicating high (≥5) versus low (≤4) credit information sharing, and **DIG** represents the degree of digitalization of bank *i*. Significance levels are indicated as *, **, and *** corresponding to the 10%, 5%, and 1% levels, respectively.

Overall, we can observe several interesting trends. Economic growth (EG) shows weak correlations with other variables such as inflation (INF), non-performing loans (NPL), and digitalization (DIG), suggesting subtle links between these factors. Indeed, the correlation coefficients are below 0.6, indicating relatively weak relationships between the financial variables studied. When all correlation coefficients are below 0.6, this suggests that the variables are not strongly linearly correlated with each other. This allows us to conclude that there is no autocorrelation problem between the variables, which will be verified by the VIF test later.

3.3.3 VIF test

Table 4: VIF test

Variable	VIF	1/VIF
NPL	2.7900	0.3584
CRINFOR	2.4800	0.4032
DIG	2.3000	0.4347
BIR	2.1000	0.4761
LIQ	2.0900	0.4784
BASSET	1.6700	0.5985
INF	1.4100	0.7078
EG	1.2000	0.8322
Mean VIF	2.0500	

Note: The table presents the Variance Inflation Factor (VIF) values for the independent variables included in the analysis, used to detect potential multicollinearity. **NPL** represents non-performing loans of bank *i* at year *t*, **CRINFOR** is the binary variable indicating high versus low credit information sharing, **DIG** captures the degree of digitalization of bank *i*, **BIR** denotes the bank interest rate, **LIQ** represents the liquidity level, **BASSET** is the size of bank *i*, **INF** is the inflation rate of country *i*, and **EG** is the economic growth rate of country *i*. The 1/VIF column provides the tolerance values, and the Mean VIF is also reported. All VIF values are below the common threshold of 10, indicating that multicollinearity is not a concern in the model.

The analysis of the VIF test results in Table 4 shows that the financial variables exhibit overall low levels of multicollinearity. The VIF values range from 1.2000 to 2.7900, with an average of 2.0500, indicating minimal influence of multicollinearity on regression coefficient estimates. The NPL and CRINFOR variables have the highest VIFs, but they remain below 3, which is generally considered acceptable. In contrast, the INF and EG variables have the lowest VIFs, suggesting little correlation with other variables in the analysis.

These results demonstrate a relative independence among the financial variables studied, strengthening the validity of the econometric models developed from this data. With multicollinearity levels below 3, the reliability of regression coefficient estimates and model predictions is enhanced. These positive findings provide a solid foundation for interpreting econometric analyses and making informed decisions based on the relationships between the financial variables under examination.

4 Results and Discussions

The impact of non-performing loans (NPLs) on the performance and financial stability of banks is a critical area of study in the banking sector. NPLs not only affect a bank's profitability but also pose significant risks to its overall stability and resilience in the face of economic fluctuations. This analysis aims to explore the intricacies of how NPLs influence key performance indicators, such as return on assets (ROA) and Z-score, while also considering the moderating effects of digitalization in enhancing risk management practices.

4.1 Stationarity Test

Table 5: Unit root test

Variable	**Levin–Lin–Chu (p-value)**	**Im–Pesaran–Shin (p-value)**	**Fisher-ADF (p-value)**	**Stationarity**
ROA	0.0050***	0.0030***	0.0070***	I(0)
ROE	0.0090***	0.0180**	0.0050***	I(0)
Zscore	0.0210**	0.0130**	0.0120**	I(0)
NPL	0.0050***	0.0080***	0.0070***	I(0)
DIG	0.0320**	0.0310**	0.0160**	I(0)
EG	0.0060***	0.0070***	0.0080***	I(0)
INF	0.0020***	0.0410**	0.0040***	I(0)
BASSET	0.0080***	0.0250**	0.0030***	I(0)
BIR	0.0180**	0.0320**	0.0230**	I(0)
LIQ	0.0070***	0.0060***	0.0070***	I(0)
CRINFOR	0.0090***	0.0080***	0.0070***	I(0)

Note: Table 5 presents the results of unit root tests conducted to examine the stationarity of the variables. The tests include Levin–Lin–Chu (LLC), Im–Pesaran–Shin (IPS), and Fisher-ADF, with p-values reported for each. **ROA** represents the return on assets, **ROE** the return on equity, and **Z-score** measures the financial stability of bank *i* at year *t*. **NPL** denotes non-performing loans, **DIG** captures the degree of digitalization, **LIQ** represents the bank's liquidity, **CRINFOR** is the binary variable indicating high versus low credit information sharing, **BASSET** is the bank size, **BIR** is the bank interest rate, **INF** is the inflation rate, and **EG** is the economic growth rate of country *i* at year *t*. The "Stationarity" column indicates whether a variable is stationary at level (I(0)). Significance levels are denoted by ***, **, and * corresponding to the 1%, 5%, and 10% levels, respectively.

To ensure the validity of the panel estimates and avoid spurious regressions, we examined the stationarity properties of all variables by applying several panel unit root tests, namely Levin–Lin–

Chu (LLC), Im–Pesaran–Shin (IPS), and Fisher-ADF. These tests were conducted by incorporating individual effects and, where appropriate, deterministic trends. The results reported in Table 5 indicate that all variables in the study—ROA, ROE, Z-score, NPL, DIG, EG, INF, BASSET, BIR, LIQ, and CRINFOR—are stationary at level, i.e., integrated of order zero (I(0)).

This finding implies that the variables do not exhibit stochastic trends, thereby mitigating the risk of spurious regression typically associated with non-stationary series. As highlighted by Cheng et al. (2021) and Wong et al. (2024), even when variables are stationary, careful diagnostic testing remains essential to ensure that estimated relationships are statistically meaningful and not driven by hidden dependencies or misspecification. In this context, the stationarity of all variables justifies the estimation of the models in levels without the need for differencing. Consequently, the fixed-effects and random-effects estimations can be considered robust and reliable, as they are not affected by spurious correlations.

Table 6. Diagnostic Tests for Panel Data Models

Test	ROA	ROE	Z-score
Jarque–Bera χ^2	2.1400 (0.3420)	1.8500 (0.3970)	2.7000 (0.2590)
Wooldridge F-test	0.9500 (0.3290)	1.1200 (0.2750)	1.0500 (0.3050)
Modified Wald χ^2	12.4500 (0.1120)	9.7800 (0.2100)	11.3500 (0.1460)

Note: Table 6 reports the results of diagnostic tests for the panel data models estimated for the dependent variables **ROA**, **ROE**, and **Zscore**. The **Jarque–Bera test** examines the normality of the residuals, with the χ^2 statistic and corresponding p-values reported in parentheses. The **Wooldridge F-test** is used to detect autocorrelation in panel data, while the **Modified Wald χ^2 test** assesses heteroskedasticity across panels. In all cases, the p-values indicate no significant violation of normality, autocorrelation, or heteroskedasticity assumptions. All variables retain their definitions as previously stated: **ROA** is return on assets, **ROE** is return on equity, and **Zscore** measures the financial stability of bank *i* in year *t*.

The results of the diagnostic tests applied to the ROA, ROE, and Z-score models are presented in Table 6. The Jarque-Bera test, designed to verify the normality of the residuals, shows low values (2.1400 for ROA, 1.8500 for ROE, and 2.7000 for Z-score) with respective p-values greater than 0.2500. These results allow us to confirm the null hypothesis of normality, indicating that the errors follow a normal distribution, an essential condition for the validity of classical statistical tests. Furthermore, the Wooldridge F-test, which assesses the presence of autocorrelation in the panel data, shows non-significant statistics with p-values greater than 0.2700, confirming the absence of autocorrelation in the residuals of the three models. Finally, the Modified Wald test, used to detect heteroscedasticity, also yields p-values above the 5% threshold, suggesting that the variance of the errors is constant across the different units of the panel. Thus, all of these findings confirm that the main classical assumptions—normality of residuals, absence of autocorrelation, and homoscedasticity—are met in the models studied. These results strengthen the robustness of the estimates and the reliability of the statistical inferences, ensuring a rigorous and credible interpretation of the financial analyses performed.

While the unit root tests presented in Table 5 confirm that all variables are stationary at level (I(0)), and diagnostic tests in Table 6 support model adequacy, it is essential to address the potential issue of spurious regression, which can sometimes arise even when variables are stationary (Granger & Newbold, 1974; Phillips, 1986). To ensure the robustness and validity of our regression results, we incorporate a discussion of nonlinearity tests following the approach of Hui et al. (2017), which help detect possible nonlinear relationships or misspecifications in the model that could bias estimates.

Table 7: Nonlinearity Tests

Variables	Nonlinearity Test Statistic (F)	p-value	Nonlinearity Issue
NPL	1.2100	0.2700	No
DIG	0.9800	0.3300	No
NPL × DIG	1.0500	0.3100	No
EG	1.1400	0.2900	No
INF	1.0900	0.3000	No
BASSET	0.9500	0.3400	No
BIR	1.0800	0.2950	No
LIQ	1.0200	0.3150	No
CRINFOR	1.1000	0.2850	No

Note: Table 7 presents the results of the nonlinearity tests following Hui et al. (2017) for all explanatory variables used in the analysis. The **Nonlinearity Test Statistic (F)** and the corresponding p-values are reported for each variable to assess whether a nonlinear relationship exists. **NPL** represents non-performing loans, **DIG** captures the degree of digitalization of bank *i*, and **NPL × DIG** represents the interaction term between non-performing loans and digitalization. **EG** denotes the economic growth rate of country *i*, **INF** is the inflation rate, **BASSET** is the size of bank *i*, **BIR** is the bank interest rate, **LIQ_{it}** represents liquidity, and **CRINFOR** is the binary variable indicating high versus low credit information sharing. The "Nonlinearity Issue" column indicates whether any nonlinearity was detected for each variable. All p-values exceed conventional significance levels, confirming that there is no evidence of nonlinearity in the model.

To ensure that the estimated model is correctly specified, we conducted the nonlinearity test proposed by Hui et al. (2017). The results, reported in Table 7, indicate that none of the explanatory variables—including NPL, DIG, their interaction term (NPL × DIG), and the control variables EG, INF, BASSET, BIR, LIQ, and CRINFOR—exhibit significant nonlinear relationships with the dependent variable. Specifically, all F-statistics range from 0.9500 to 1.2100, and all corresponding p-values exceed the conventional 0.0500 significance level, indicating that the null hypothesis of linearity cannot be rejected.

These findings suggest that the linear specification of the model is appropriate, and the estimated coefficients can be interpreted without concern for misspecification due to non-linear effects. Consequently, the model provides a reliable framework for analyzing the effects of credit risk, digitalization, and other key factors on bank performance.

Finally, given the use of correlation and regression analysis, we explicitly recognize the limitations related to causality inference. While the dynamic panel GMM technique employed helps mitigate endogeneity concerns and capture temporal dynamics, it cannot conclusively prove causal effects without additional identification strategies. Therefore, results should be interpreted as indicative of associations and moderating effects rather than definitive causal links.

Table 8: The effect of non-performing loans and the performance and financial stability of banks

	ROA			**ROE**			**Z-score**		
	Coefficient	**z**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**z**	**p-value**
NPL	-0.0094	-2.8800	0.0040 ***	-0.0372	-2.8700	0.0040 ***	-0.4670	-5.5100	0.0000 ***

CRINFOR	0.0733	3.7300	0.0000 ***	0.6215	3.6200	0.0000 ***	-0.1592	-0.3100	0.7550
LIQ	0.0091	1.6700	0.0940 *	0.9337	6.5600	0.0000 ***	0.1052	0.2400	0.8110
BIR	0.2212	2.5600	0.0100 **	0.1466	3.0600	0.0020 ***	11.1894	4.9900	0.0000 ***
BASSET	-0.0021	-1.4300	0.1520	0.1995	1.3500	0.1770	0.2285	5.9300	0.0000 ***
INF	-0.0366	-1.8500	0.0640*	-0.1990	-1.1500	0.2500	0.0691	0.1300	0.8930
EG	0.0390	2.2500	0.0250**	0.3464	2.2800	0.022**	-0.1175	-0.2600	0.7940
R2	0.6047			0.6616			0.4925		
Fisher	97.6800 0.0000***			104.4500 0.0000***			207.9100 0.0000***		

Notes: This table reports **panel data** estimation of the effect of non-performing loans on bank performance and financial stability, based on **Equations 1 – 3,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies financial stability. **NPL** is the non-performing loans to total loans. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *****, ******, and ******* denote significance at the **10%**, **5%**, and **1%** levels, respectively.

The econometric analysis of the effects of non-performing loans (NPLs) on bank performance and financial stability, as measured by ROA (Return on Assets) and Z-score, as shown in Table 8, reveals significant results. The coefficients associated with NPLs are negative and statistically significant in all specifications, indicating that an increase in non-performing loans is associated with a decrease in bank financial performance. Specifically, a coefficient of -0.0094 for ROA suggests that a one-unit increase in NPLs leads to a 0.0094 -point decrease in ROA, which is significant at the 1% level ($p < 0.01$). Similarly, for the Z-score, the coefficient of -0.4670 indicates that banks with higher levels of NPLs exhibit reduced financial stability, which is also significant ($p < 0.001$). These results corroborate the findings of recent studies that highlight the negative impact of NPLs on the financial health of banking institutions. For example, Beck et al. (2013) showed that non-performing loans can affect the ability of banks to generate profits and maintain adequate capital levels, which is essential for their long-term stability. Furthermore, research by Babalos et al. (2015) highlighted that banks with high levels of NPLs are often perceived as riskier by investors, which can lead to increased funding costs and pressure on profit margins.

With respect to other variables, the capital ratio (BIR) also shows a significant effect. The positive coefficient of 0.2212 for BIR indicates that an increase in capital is associated with better performance, which is in line with the theory that higher capital can absorb losses and reduce the risk of bankruptcy. In contrast, variables such as liquidity (LIQ) and inflation (INF) do not show significant effects on ROA or Z-score, which could indicate that, in the current context, these factors do not have a direct impact on bank performance and stability. This could also reflect specific market conditions where other factors, such as NPL management, take precedence over liquidity and inflation considerations.

Indeed, the results of this analysis highlight the importance of NPL management for bank performance and financial stability. Banks should therefore implement effective strategies to reduce NPLs in order to improve their profitability and resilience to economic shocks.

Table 9: The effect of digitalization on the performance and financial stability of banks

	ROA			ROE			Z-score		
	Coefficient	**t**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**Z**	**p-value**
DIG	3.8934	2.5300	0.0050***	0.9108	3.0000	0.0030***	0.3052	1.8000	0.0730*
CRINFOR	12.4702	0.7200	0.5120	6.5252	1.8000	0.0720*	3.1257	1.5400	0.1230
LIQ	0.5577	1.9700	0.0490**	1.6028	1.6600	0.0960*	1.4667	2.7200	0.0060***
BIR	-6.9582	-0.9600	0.3890	4.4032	1.7100	0.0870*	0.1827	0.1300	0.8990
BASSET	0.3306	1.2900	0.2650	0.0767	0.7900	0.4290	0.0524	0.9700	0.3330
INF	-35.8909	-2.0500	0.0400**	-0.0178	-1.6600	0.0960*	-0.0163	-2.7300	0.0060***
EG	1.4171	1.3000	0.2640	0.3401	0.9800	0.3270	0.02116	0.1100	0.9130
R2	0.7394			0.4958			0.3590		
Fisher	44.2600 0.0000***			326.4400 0.0000***			204.3700 0.0000***		

Notes: This table reports **panel data** estimation of the effect of digitalization on bank performance and financial stability, based on **Equations 4 – 6,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies financial stability. **L1.** denotes the lagged dependent variable. **NPL** is the non-performing loans to total loans. **DIG** denotes digitalization. **NPL×DIG** captures the moderating effect of digitalization. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *, **, and *** denote significance at the **10%**, **5%**, and **1%** levels, respectively.

The results of the analysis in Table 9 highlight several key points regarding the impact of digitalization and other variables on bank performance and financial stability. In particular, the digitalization variable (DIG) shows a positive and significant effect on bank performance (ROA, ROE) and financial stability (Z-score) measures. This finding is in line with a series of recent studies that highlight the growing importance of digitalization in the banking sector. For example, Jia and Liu (2023) highlighted how investments in digital technologies have led to notable improvements in bank profitability and risk management capabilities.

Regarding other variables, liquidity (LIQ) has also shown a significant effect on bank performance and financial stability. Recent research by Chen et al. (2024) has highlighted the importance of effective liquidity management in the current financial environment, with direct links between optimal liquidity levels and strong bank performance. Similarly, inflation (INF) has been identified as having an impact on bank performance. A recent study by Awdeh et al. (2024) examined how inflation can influence the financial stability of banks, highlighting complex mechanisms that require in-depth analysis.

These findings underscore the critical importance of digitalization and other key variables for the financial health of banks. The cited studies offer additional insights into these relationships and highlight the increasing relevance of these factors in a rapidly changing banking environment. By continuing to explore these areas of research, it is possible to deepen our understanding of the underlying dynamics that shape the performance and stability of financial institutions in the digital age.

Table 10: The moderating effect of digitalization between non-performing loans and banks' performance and financial stability

	ROA			ROE			Z-score		
	Coefficient	**z**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**z**	**p-value**
NPL	-0.1056	-0.7100	0.4760	-1.8961	-1.0700	0.3050	-4.9205	-1.9100	0.0560*
DIG	0.0081	0.2400	0.8130	-0.3455	-1.0000	0.3380	0.0286	2.9400	0.0030 ***
NPL*DIG	0.7592	5.0800	0.0000 ***	0.0068	2.2900	0.0410**	0.2139	2.4200	0.0160**
CRINFOR	0.0323	1.9600	0.0460**	0.3427	1.6400	0.1270	-0.1469	-0.3000	0.7620
LIQ	0.0080	1.9800	0.0390**	0.0372	1.9600	0.0490**	0.8204	4.5300	0.0000 ***
BIR	0.0026	0.5300	0.5990	5.6745	4.0000	0.0020***	10.9756	4.2300	0.0000 ***
BASSET	0.0005	0.2200	0.8300	0.0228	0.4400	0.6690	0.1428	3.0600	0.0020 ***
INF	-0.0172	-0.7200	0.4730	-0.3343	-1.8400	0.0910*	-0.0126	-2.2700	0.0230**
EG	0.0309	1.8600	0.0630*	0.0378	0.2600	0.8000	0.5647	3.5800	0.0000***
R2	0.6345			0.7621			0.8060		
Fisher	97.1800 0.0000***			2.9600 0.0348**			3.8300 0.0131**		

Notes: This table reports **panel data** estimation of the moderating effect of digitalization on the relationship between non-performing loans and bank performance and financial stability, based on **Equations 7 – 9,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies financial stability. **NPL** is the non-performing loans to total loans. **DIG** denotes digitalization. **NPL×DIG** captures the moderating effect of digitalization. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *****, ******, and ******* denote significance at the **10%**, **5%**, and **1%** levels, respectively.

The results of the models in Table 10 demonstrate that digitalization plays a crucial role as a moderating factor between non-performing loans (NPLs) and bank performance. In the model based on return on assets (ROA), the interaction between NPLs and digitalization (NPLDIG) is significant, indicating that digitalization helps mitigate the negative impact of NPLs on performance. While NPLs alone do not significantly affect ROA, digitalization enhances their management. The ROE model also supports this trend, showing that digitalization positively moderates the impact of NPLs, even though NPLs themselves do not have a direct, significant effect.

In terms of financial stability measured by the Z-score, digitalization has a significant positive effect, bolstering banks' resilience against the risks associated with NPLs. The R^2 coefficients for all three models are high (0.6345, 0.7621, and 0.8060), indicating a strong explanatory power of the models. Fisher tests yield significant results, confirming the statistical validity of the overall models. These findings align with recent studies by Kou et al. (2024) and Chen et al. (2023), emphasizing the importance of digitalization in enhancing risk management and banking performance.

4.2 Robustness Check

The Generalized Method of Moments (GMM) is recognized for its robustness in estimating econometric models, making it a preferred choice for many applications. One of the main advantages of GMM is its ability to provide reliable estimates even in the presence of violations of classical assumptions, such as heteroscedasticity and autocorrelation. This means that the results obtained are less sensitive to fluctuations and data anomalies, thus strengthening their validity.

Furthermore, GMM allows the use of instruments that can correct for endogeneity, thus ensuring that estimates are not biased by omitted variables or measurement errors. This flexibility in the choice of instruments contributes to the robustness of the results, providing room to adapt the model to the specificities of the data. Finally, the GMM method is capable of incorporating moments of different orders, which improves the efficiency of the estimations.

To ensure the robustness of the empirical results, this study employs the dynamic panel Generalized Method of Moments (GMM) estimator. First, GMM effectively addresses the endogeneity of non-performing loans (NPLs), which may arise from reverse causality (bank performance influencing NPL levels), simultaneity, and omitted variable bias. Second, the inclusion of the lagged dependent variable captures the dynamic persistence of bank performance and financial stability, while GMM corrects for the resulting dynamic panel bias that would affect fixed-effects or OLS estimators. Third, GMM controls for unobserved bank-specific heterogeneity and exploits internal instruments constructed from lagged values of the endogenous variables, thereby improving estimator consistency and efficiency. For these reasons, GMM provides more reliable and consistent estimates than conventional panel techniques in the presence of endogenous regressors and dynamic relationships.

Indeed, we will use this method to confirm the results obtained using the static panel method.

Table 11: The effect of non-performing loans and the performance and financial stability of banks using GMM

	ROA			**ROE**			**Z-score**		
	Coefficient	**z**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**z**	**p-value**
L1	0.4369	4.1200	0.0000***	0.4596	3.9500	0.0000***	0.8562	3.6700	0.0000***
NPL	-0.7534	-4.0700	0.0000***	-0.6051	-4.8700	0.0000***	-4.1746	-2.9500	0.0030***
CRINFOR	0.0139	1.8200	0.0700*	0.0380	5.4100	0.0000***	-0.0317	-1.800	0.0720*
LIQ	0.0331	4.9900	0.0000***	0.0372	5.3800	0.0000***	0.3474	0.9700	0.3320
BIR	0.0318	1.8300	0.0680*	-0.4220	-2.0600	0.0390**	6.4611	7.2600	0.000***
BASSET	-0.8352	-0.9500	0.3410	0.1995	1.3500	0.1770	0.0628	1.6600	0.0970*
INF	-0.3339	-1.7400	0.0820*	-0.0885	-1.8200	0.0690*	-0.0513	-0.2000	0.8430
EG	0.0606	1.6000	0.1100	0.0091	0.2300	0.8140	-0.3200	-1.6700	0.0950*

Notes: This table reports **system GMM** estimates of the effect of non-performing loans on bank performance and financial stability, based on **Equations 1 – 3,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies financial stability. **L1.** denotes the lagged dependent variable. **NPL** is the non-performing loans to total loans. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *****, ******, and ******* denote significance at the **10%**, **5%**, and **1%** levels, respectively.

Table 11 presents the results of an analysis using the generalized model of moments (GMM) to assess the impact of non-performing loans (NPLs) on bank performance and financial stability, measured by three indicators: return on assets (ROA), return on equity (ROE), and Z-score.

First, the analysis shows that non-performing loans have a significant and negative impact on all three performance indicators. For ROA, the coefficient of -0.7534 indicates that a 1-unit increase in NPLs is associated with a 0.75-unit decrease in ROA, with significance at the 1% level ($p<0.001$). Similarly, for ROE, the coefficient of -0.6051 also shows a significant reduction in ROE in response to an increase in NPLs, which is also significant at the 1% level. Finally, for the Z-score, which measures solvency and stability, the coefficient of -4.1746 suggests that rising NPLs significantly reduce banks' financial stability, with significance at the 5% level.

Next, regarding the other variables, the credit information ratio (CRINFOR) has a positive effect on ROE and a marginally significant effect on ROA, indicating that higher credit information levels can contribute to better bank performance. However, its impact on the Z-score is negative and close to significance, which could indicate complex effects on financial stability. Liquidity (LIQ) shows a positive and significant impact on ROA and ROE, but its effect on the Z-score is not significant, suggesting that liquidity is crucial for performance but has no direct effect on solvency.

Regarding the bank interest rate (BIR), its impact is varied. It has a positive effect on the Z-score, reinforcing the idea that higher interest rates can improve stability, while its effects on ROA and ROE are mixed. The inflation (INF) and economic growth (EG) variables appear to have less consistent effects, with insignificant coefficients for the Z-score, but impacts close to significance on ROA and ROE. These results are consistent with those found using the static panel method, which reinforces our results.

Table 12: The effect of digitalization on the performance and financial stability of banks using GMM

	ROA			**ROE**			**Z-score**		
	Coefficient	**t**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**Z**	**p-value**
L1.	0.0321	6.1500	0.0000***	0.0119	2.4800	0.0130**	0.0198	4.0200	0.0000***
DIG	1.3139	3.4200	0.0000***	0.0326	4.9100	0.0000 ***	0.0341	1.8600	0.0630*
CRINFOR	1.3611	0.9500	0.3400	6.7086	3.8400	0.0020 ***	1.5782	1.5000	0.1340
LIQ	0.4017	1.9900	0.0470**	1.6668	3.1500	0.0060 ***	1.4171	2.0000	0.0460**
BIR	-0.0957	-1.9800	0.0480**	3.3627	1.8200	0.0870*	0.5782	1.5600	0.1290
BASSET	0.3306	1.2900	0.2650	0.0693	0.4000	0.6870	0.0421	1.0400	0.2970
INF	-32.8126	-2.3300	0.0250**	-0.0440	-1.1400	0.2540	-0.0940	-1.9900	0.0460**
EG	1.3627	1.0200	0.3070	0.3401	0.9800	0.3270	0.0427	0.2400	0.8100

Notes: This table reports **system GMM** estimates of the effect of digitalization on bank performance and financial stability, based on **Equations 4 - 6,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies financial stability. **L1.** denotes the lagged dependent variable. **DIG** denotes digitalization. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *****, ******, and ******* denote significance at the **10%**, **5%**, and **1%** levels, respectively.

Table 12 examines the impact of digitalization on bank performance and financial stability using the Generalized Method of Moments (GMM), focusing on three indicators: return on assets (ROA), return on equity (ROE), and Z-score. First, it is essential to note the significant positive impact of digitalization (DIG) on all performance indicators. For ROA, the coefficient of 1.3139 indicates that an increase in digitalization is associated with a 1.3100 unit increase in ROA, with significance at the 1% level (p<0.001). This suggests that digitalization initiatives significantly improve bank efficiency. Similarly, for ROE, the coefficient of 0.032615 also shows a significant increase, indicating that digitalization strengthens banks' return on equity. Although the effect on the Z-score is positive (0.0341) and close to significance (p=0.063), it remains less pronounced than for the other measures, which could indicate that the impact on financial stability is present but requires other factors to be fully significant.

Regarding the other variables, the credit information ratio (CRINFOR) has a significant effect on ROE, with a coefficient of 6.7086, highlighting the importance of good credit information for bank performance. However, its effect on ROA is insignificant, which may suggest that short-term profitability is not directly influenced by capital. Liquidity (LIQ) also proves crucial, with positive and significant coefficients for all three indicators, indicating that high liquidity levels are associated with better performance and greater financial stability. In contrast, the bank interest rate (BIR) has a negative impact on ROA, with a coefficient of -0.0957, indicating that higher interest rates can harm profitability. However, its effect on ROE is marginally significant (p=0.0870), while its influence on the Z-score remains insignificant. The inflation (INF) and economic growth (EG) variables show mixed effects. Inflation has a significant negative impact on ROA and Z-score, suggesting that high inflation levels can harm bank performance and stability. In contrast, economic growth does not show a significant effect on the indicators examined. Indeed, our results illustrate the growing importance of digitalization in improving bank performance. The results highlight the need for financial institutions to adopt digital technologies to strengthen their profitability and efficiency while highlighting the complex effects of other economic factors on financial stability. These results are consistent with those found using the static panel method, which reinforces our results.

Table 13: The moderating effect of digitalization between non-performing loans and banks' performance and financial stability using GMM

	ROA			ROE			Z-score		
	Coefficient	**z**	**p-value**	**Coefficient**	**z**	**p-value**	**Coefficient**	**z**	**p-value**
L1.	0.0354	5.2500	0.000***	0.6836	3.5700	0.0000 ***	0.7615	3.6800	0.0000 ***
NPL	-0.0247	-1.4500	0.1490	-0.0259	-1.5400	0.1240	-1.3887	-2.0300	0.0420 **
DIG	0.0031	0.7100	0.4810	-0.1056	-0.4100	0.6800	0.0413	3.9300	0.0000 ***
NPL*DIG	0. 4495	6.2900	0.0000***	0.0323	4.9200	0.0000**	1.0728	2.0900	0.0370 **
CRINFOR	0.0874	1.7400	0.0820*	0.4018	1.1400	0.2530	-0.0516	-1.3800	0.1700
LIQ	0.0665	1.7000	0.0890*	0.3712	1.7900	0.0740*	0.3126	4.9400	0.0000 ***
BIR	0.0021	0.6600	0.5090	2.6657	1.7300	0.0830*	1.4232	3.6900	0.0000 ***
BASSET	0.0201	0.5000	0.6190	0.0277	0.6900	0.4870	0.3052	1.6700	0.0950*
INF	-0.0310	-1.4800	0.1390	-0.0946	-1.9100	0.0560*	-0.0472	-2.3000	0.0210 **
EG	0.3479	1.8400	0.0660*	0.0587	0.2100	0.8320	0.9108	1.6800	0.0930*

Notes: This table reports **system GMM** estimates of the moderating effect of digitalization on the relationship between non-performing loans and bank performance and financial stability, based on **Equations 7 – 9,** where **ROA** and **ROE** measure bank performance, and **Z-score** proxies' financial stability. **L1.** denotes the lagged dependent variable. **NPL** is non-performing loans to total loans. **DIG** denotes digitalization. **NPL×DIG** captures the moderating effect of digitalization. **CRINFOR** is credit information depth, **LIQ** is liquidity, **BIR** is the bank interest rate, **BASSET** is bank size (log of total assets), **INF** is inflation, and **EG** is economic growth. z-statistics and p-values are reported. *****, ******, and ******* denote significance at the **10%**, **5%**, and **1%** levels, respectively.

Table 13 explores the moderating effect of digitalization on the relationship between non-performing loans (NPLs) and bank performance and financial stability using the generalized model of moments (GMM). The results presented for the three indicators—return on assets (ROA), return on equity (ROE), and Z-score—reveal interesting dynamics, particularly the interaction between NPLs and digitalization.

First, the direct effect of non-performing loans (NPLs) on ROA and ROE is negative, although insignificant in this context, with coefficients of -0.0247 and -0.0259, respectively. This suggests that NPLs tend to harm bank performance, but the lack of statistical significance indicates that this effect could be mitigated by other factors. In contrast, the interaction between NPLs and digitalization (NPL*DIG) has a significant positive coefficient of 0.4495 for ROA, indicating that digitalization can mitigate the negative impact of NPLs on bank profitability. This phenomenon is also observed for ROE, where the coefficient is 0.0323, highlighting that, thanks to digitalization, banks can better manage their non-performing loans and thus improve their performance.

Regarding the Z-score, which measures solvency and financial stability, the moderating effect of digitalization is also significant, with a coefficient of 1.0728. This indicates that digitalization strengthens banks' ability to maintain their financial stability even in the presence of non-performing loans, which is indicative of more efficient and resilient management. Regarding the other variables, the capitalization ratio (CRINFOR) shows a positive trend approaching significance for ROA (0.0874), while liquidity (LIQ) has a positive and significant effect on ROA, ROE, and Z-score, reinforcing the idea that liquidity management is crucial for bank performance. The bank interest rate (BIR) shows a significant effect on ROE, but its impact on ROA and Z-score is inconclusive. The effects of inflation (INF) and economic growth (EG) show coefficients approaching significance, indicating complex relationships that deserve careful attention.

Our results highlight the essential role of digitalization as a moderating factor in the relationship between non-performing loans and bank performance. The results suggest that financial institutions that invest in digital solutions can not only improve their profitability but also strengthen their financial stability in the face of challenges such as non-performing loans. This highlights the importance of digital transformation in the modern banking sector, providing opportunities to mitigate the risks associated with bad loans. These results are consistent with those found using the static panel method, which reinforces our findings.

5. Conclusion

Motivations and Issues

Non-performing loans (NPLs) are crucial indicators of banks' financial health. A high level of NPLs can indicate liquidity and solvency issues, impacting bank performance and overall financial stability. Rigorous management is necessary to prevent systemic risks and financial crises. Reducing NPLs is essential to free up financial resources and support economic growth. Simultaneously, banking digitalization is reshaping the financial landscape by enhancing operational efficiency and providing superior services to customers. It enables more efficient risk management, including NPLs, through automation and advanced data analytics. Digitalization also facilitates access to new markets and strengthens banks' competitiveness amidst technological advancements.

Summary of Main Results

The results demonstrate that NPLs pose a significant challenge for banks by tying up financial resources and increasing the risk of losses. In MENA countries, where economies are susceptible to external shocks, a high level of NPLs can hinder banks' ability to lend, limiting economic development. Digitalization plays a crucial role in mitigating these adverse effects, thereby enhancing banks' resilience to economic shocks. Our findings emphasize that digitalization serves as an effective moderator by reducing operational costs and enhancing risk management. With digital technologies, banks can better analyze customer data, predict defaults, and optimize loan recovery, enabling a quicker and more targeted response to potential NPL issues. Integrating digital tools such as artificial intelligence and big data strengthens banks' capacity to identify early signals of financial distress, improving both NPL management and overall bank performance.

Importance and Usefulness for the Academic Community and Practitioners

This study enriches existing literature by integrating the concepts of non-performing loans, bank performance, and digitalization. By addressing these themes holistically, it provides an overview of how digitalization can alleviate the negative impacts of non-performing loans. The development of a theoretical model linking digitalization to NPL management offers a deeper understanding of the underlying mechanisms. This model can serve as a foundation for future research by proposing testable hypotheses on the relationship between these variables. The findings offer practical recommendations for financial institutions seeking to enhance their NPL management and underscore the significance of digital innovation. For practitioners, this highlights the importance of investing in appropriate technologies, such as data analytics and automation, to optimize operations and improve risk management. Regulators can also benefit by promoting policies that encourage digital transformation to bolster overall financial stability.

Original Contributions

This study presents original evidence on the moderating role of digitalization in the relationship between non-performing loans and bank performance and stability, based on a long-term panel analysis of 18 MENA countries over 24 years. Unlike previous short-term or country-specific studies, it provides a comprehensive regional perspective and develops a theoretical framework linking digitalization and NPL management. The inclusion of digitalization as a moderator in the empirical models advances the literature by illustrating how technological investments can strengthen banks' financial resilience in emerging markets.

Limitations and Avenues for Future Research

Despite these contributions, this research has some limitations that present opportunities for future exploration. The study's scope is confined to aggregate banking sector data in MENA countries, which may obscure variations across specific types of banks or loan segments. Future studies could concentrate on specific sectors such as consumer or commercial lending to investigate whether the effects of digitalization vary by debt type. Further research could also delve into emerging technologies like blockchain or advanced machine learning algorithms and their potential to revolutionize NPL management and enhance bank performance. Additionally, extending the analysis to other performance dimensions, including operational efficiency and sustainability, would deepen the understanding of digitalization's multifaceted impact. Such studies would enrich the existing literature and aid in the formulation of more targeted digital strategies in banking.

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