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The Impact of Digital Transformation on Risk-Taking of Commercial Banks in Indonesia

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Abstract: Background: Progress in digital technology has prompted commercial banks to undergo digital transformation to improve operational efficiency and consolidate risk management measures. The empirical relationship between bank risk-taking and digital transformation is however inconclusive and subject to contingencies. Purpose: The study aims to examine the effect of digital transformation on credit risk (Non-Performing Loan/NPL), insolvency risk (Z-score), and liquidity risk (Loan-to-Deposit Ratio/LDR) at Indonesian commercial banks during the period from 2014 to 2024. Design/methodology/approach: This study employs the quantitative technique of panel data regression of 10 Indonesian commercial banks. The Analytic Hierarchy Process (AHP) method is also employed to determine the priority between risk indicators affected by digital transformation in order to guarantee methodological triangulation. Findings/Result: The regression result indicates that digital transformation is statistically negatively correlated with credit risk (NPL), although the correlation is not significant at the 5% level. No significant relationship comes out of Z-score and LDR. AHP results identify that NPL has the highest priority weight of 0.7445, indicating that digital transformation activities are primarily focused on mitigating credit risk. Conclusion: Digitalization of Indonesian commercial banks could potentially reduce credit risk but needs further strengthening and testing to obtain statistically significant outcomes. Emphasis on NPL in AHP analysis highlights the strategic importance of credit risk management in digitalization. Originality/value (State of the art): This study contributes to the exceedingly small empirical literature on the impact of digital transformation on risk-taking in emerging banking markets. It combines econometric and decision-making approaches (regression and AHP) for a first-of-its-kind, combined look at the way digital initiatives prioritize different types of banking risks.

Keywords: digital transformation, risk-taking, Non-Performing Loan, Z-score, Loan-to-Deposit Ratio, AHP, Indonesian commercial banks.

INTRODUCTION

Digitalization has become a dominant paradigm of the global banking industry's modernization, as in Indonesia. The emergence of mobile banking, internet banking, and application of big data and artificial intelligence has revolutionized banking operations, extended the reach of services, and enhanced the efficiency of transactions. As highlighted by Bank Indonesia (2023), digital banking transactions in Indonesia increased 158% from 2018 to 2023, indicative of robust consumer demand for digital financial services. In line with this, the Financial Services Authority (OJK) unveiled the Digital Banking Transformation Blueprint in 2021 as a strategic blueprint to enable systemic and measurable embrace of digital technology among the national banking sector (OJK, 2021).

While there are numerous benefits of digital transformation in banking efficiency and in financial inclusion, it also has implications for the financial system's stability, particularly that of the risk-taking behavior of banks. Risk-taking is defined by Stulz (2015) as a strategy that increases exposure to credit risk, insolvency risk, and liquidity risk. On the positive side, technology adoption would boost risk management channels through data processing in real time and portfolio monitoring on an auto-pilot basis. Conversely, competitive forces and the imperative for innovation in the digital economy may compel expansionist inclinations that usher in new risks (Zhu et al., 2023).

Previous studies have yielded inconclusive evidence on the relationship between digital transformation and risk-taking. Hoque et al., (2024) determined that bank digitalization reduces credit and insolvency risks but has a small impact on the risk of liquidity. Fan et al., (2024) and Li & Zhang (2024) corroborated this by observing that the efficiency that digital technologies encourage in operations has the ability to neutralize risk-taking behaviors. On the other hand, studies by Dai et al., (2023) and Feng & Yu (2024) posit that digitalization will augment risk-taking, especially within organizations that face intense competition and intense innovation pressure. These results are diametrically opposite since the impacts of digital transformation on risk-taking were found to be contingent on the quality of governance, infrastructure readiness, and organizational characteristics (Liang et al., 2023; Sang et al., 2024).

In the Indonesian case, empirical research specifically looking at the effect of digital transformation on bank risk-taking is still scarce. Local literature mostly addresses topics such as efficiency, customer activity, or satisfaction, not addressing thoroughly how digitalization influences the three major risk types—credit, insolvency, and liquidity—together. Besides, the prevailing methodological approaches are normally descriptive or half-quantitative, without judgmental triangulation such as the Analytic Hierarchy Process (AHP), which could potentially shed more light on risk prioritization in the digital transformation agenda (Fan et al., 2024; Hoque et al., 2024; Sidorova et al., 2022).

Against these lacunae, this study aims to provide theoretically and practically significant contributions to the body of knowledge on digitalization in banking risk management. Theoretically, this research combines Institutional Theory (Scott, 2015) and Resource-Based View (Harrison et al., 2019) principles to explain the mechanism between institutional pressures from outside, organizational capabilities, and risk-taking activities. In practice, the study seeks to deliver evidence-based policy recommendations to industry players and regulators on the line of adaptive and sustainable digital risk management frameworks.

Specifically, this study's research goals are: (1) to evaluate the effect of digital transformation on Indonesian commercial bank credit risk; (2) to evaluate the effect of digital transformation on insolvency risk; and (3) to evaluate the effect of digital transformation on liquidity risk. Utilizing a quantitative panel data approach from 2014–2024 and corroborated using the AHP methodology, this research aims to provide a comprehensive understanding of digitalization's strategic position within providing national financial system stability.

METHOD

This study employed a quantitative design using secondary panel data to analyze the impact of digital transformation on risk-taking behavior of Indonesian commercial banks. The observations span ten commercial banks with yearly observations for 2014 through 2024, purposively chosen based on data availability and consistency over time. Data were collected using documentation techniques from publicly available annual reports, accounts, the Indonesian Banking Statistics of the Financial Services Authority (OJK), and macroeconomic statistics provided by Bank Indonesia.

The variable of digital transformation was proxied through a composite index that comprised several observable measures, including digital transactions volume, number of mobile banking users, expenditure on IT, and ratio of branch reduction. Furthermore, the Digital Maturity Index as constructed by OJK (2023) in Circular Letter No. 24/SEOJK.03/2023 was employed where data were available. This aligns with the institutional digital readiness measurement framework established by regulatory authorities (OJK, 2023).

Three risk-taking proxies make up the dependent variables: (1) credit risk as measured by the Non-Performing Loan (NPL) ratio, (2) insolvency risk as measured by the Z-score, and (3) liquidity risk as measured by the Loan-to-Deposit Ratio (LDR). The Z-score was calculated through the following formula (Laeven & Levine, 2009):

$$Z - Score = \frac{ROA + \frac{Equity}{Assets}}{\sigma(ROA)}$$

σ(ROA) is the standard deviation of return on assets over the sample period. Several control variables were included to prevent omitted variable bias, including firm size (log of total assets), Capital Adequacy Ratio (CAR), Return on Assets (ROA), credit growth, CASA ratio, GDP growth, and central bank interest rate. These controls have been widely used in the prior banking risk literature to determine the precise effect of digital transformation (Fan et al., 2024).

The main analysis method is panel data regression, both fixed effects and random effects models. To determine the most appropriate model, the Hausman test was applied to test whether individual effects are correlated with explanatory variables (Baltagi, 2015). The general regression equation is given below:

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 Digital_{it} + \beta_2 X_{it} + \varepsilon_{it}$$

Where Y_it is the dependent variable for bank i at time t; Digital_it is the digital transformation index; X_it is the vector of control variables; alpha_i is the unobserved bank-specific effect; lambda_t is the year fixed effect; and epsilon_it is the error term.

In addition to this, the current study employs the Analytic Hierarchy Process (AHP) as a complementary decision-support method to establish the relative importance of each risk aspect. AHP, which was established by Lande et al., (2023), employs pairwise comparisons to arrive at weights for every criterion—in this case, credit risk, insolvency risk, and liquidity risk—based on expert opinion. AHP presents a structured and replicable approach to decision-making in complex scenarios such as digital transformation in risk management (Sidorova et al., 2022).

Figure 1 shows this study's conceptual framework. It displays the hypothesized relationships between digital transformation and the three types of bank risks, after adjusting for firm-specific and macroeconomic factors.

Hypothesis

The study employs the Institutional Theory (Scott, 2015) and the Resource-Based View (Barney, 2015) in developing its hypotheses. With the Institutional Theory, it is external influences such as regulation and technological change that compel organizations to implement changes in their strategies, including risk management. With the Resource-Based View, however, internal capabilities—such as digital infrastructure—must be considered as critical resources in seeking competitive advantage while limiting exposure to risk.

More and more literature has addressed the relationship between digital transformation and bank risk-taking, and results have been diverse. While some research indicates digital transformation translates into lower risk, some studies indicate otherwise. Hoque et al. (2024) confirmed that digital initiatives at Vietnamese banks reduced credit and insolvency risk significantly but had no statistically significant effect on decreasing liquidity risk. Similarly, Li & Zhang (2024) reported that digital transformation curbed overall risk-taking by means of enhanced operating efficiency and reduced management costs. Fan et al. (2024) also confirmed a decline in systemic risk among Chinese commercial banks due to digitalization, indirectly mediated by increased operating efficiency.

Converse results point to the probability that digital transformation could promote riskier behavior. Dai et al. (2023) concluded that digitalization increased the risk-taking level, especially that of private and technology-intensive companies. Feng & Yu (2024) also established that managerial abilities complemented the risk-taking effect of digitalization, particularly against the backdrop of policy uncertainty. Studies by Sang et al., (2024) and Liu et al., (2023) further emphasized that digital innovation would enhance exposure to risk in settings that prioritize growth and innovation, suggesting that the effects of digital transformation may be context-dependent.

Despite the literature at hand, studies focusing on Indonesian commercial banks in particular and incorporating panel quantitative data in conjunction with evaluation methods like the Analytic Hierarchy Process (AHP) are not common, if not non-existent. This study attempts to fill this gap through examining the differential effect of digitalization on credit risk, insolvency risk, and liquidity risk.

Therefore, hypotheses to be tested are as follows:

H1: Digital transformation has significantly an adverse effect on credit risk (as measured by NPL) in Indonesian commercial banks, as shown by Hoque et al. (2024), Fan et al. (2024), and Li & Zhang (2024).

H2: Digital transformation has significantly an adverse effect on insolvency risk (as measured by Z-score) in Indonesian commercial banks, in line with Hoque et al. (2024) and Fan et al. (2024).

H3: There is a significant negative effect of digital transformation on liquidity risk (as measured by LDR) among Indonesian commercial banks, though previous research such as Hoque et al. (2024) show the effect is not statistically significant and there should be more research conducted in Indonesia.

RESULTS AND DISCUSSION

Descriptive Statistics

The descriptive statistics presented in Table 1 provide an overview of the distribution, central tendency, and variance of the primary variables used in this study. These are the Digital Transformation Index, Non-Performing Loan (NPL) ratio, Z-Score (as a proxy for insolvency risk), Loan-to-Deposit Ratio (LDR), and Bank Size in logarithmic form. Observations consist of 230 for 10 commercial banks listed in Indonesia from 2014 to 2024.

Table 1. Descriptive Statistics

	DIGITAL_INDEX	NPL	Z_SCORE	LDR	SIZE
Mean	0.705783	2.553174	46.97330	90.11213	17.47522
Median	0.715000	2.600000	47.32500	90.16000	17.41500
Maximum	0.950000	3.500000	59.91000	99.99000	18.99000
Minimum	0.460000	1.540000	35.16000	80.24000	16.04000
Std. Dev.	0.148847	0.579576	7.347763	5.798325	0.832575
Skewness	-0.062190	-0.119161	-0.032016	-0.016737	0.089614
Kurtosis	1.639671	1.814411	1.745443	1.785635	1.862892
Jarque-Bera	17.88218	14.01485	15.12262	14.14310	12.69923
Probability	0.000131	0.000905	0.000520	0.000849	0.001747
Sum	162.3300	587.2300	10803.86	20725.79	4019.300
Sum Sq. Dev.	5.073609	76.92298	12363.62	7699.110	158.7383
Observations	230	230	230	230	230

The Digital Transformation Index is 0.7058 with a standard deviation of 0.1488, indicating that it has moderate variation over time and banks. The index ranges from the minimum value of 0.460 up to the maximum of 0.950, reflecting heterogeneity in digital technology take-up among Indonesian banks. The distribution is nearly symmetrical, as shown through the value of the skewness of close to zero (−0.062), and Jarque-Bera test statistic (17.88; $p < 0.01$) confirms that the variable is very much not normally distributed.

The average NPL ratio is 2.55%, which represents relatively low credit risk levels in the observed banks, but the values range from 1.54% to 3.5%. The distribution is also almost symmetrical (skewness = −0.119), but the kurtosis is lower than 3 (1.81), which indicates a flat distribution. The Jarque-Bera test (14.01; $p < 0.01$) also confirms non-normality in the data distribution. This indicates the presence of small outliers or heavy tails, and these can impact regression estimates if not properly handled.

For the Z-Score, which reflects insolvency risk, the mean is 46.97 and the standard deviation is 7.35. This variable is also nearly normally distributed with minimal skewness (−0.032) and low kurtosis (1.75). However, the Jarque-Bera test (15.12; $p < 0.01$) indicates non-normality, therefore, careful interpretation must be used in inferential analysis. The greater the Z-Score, typically, the more solvency there is and less chance of bank default.

The average Loan-to-Deposit Ratio (LDR) is 90.11%, indicating that banks lend 90% on average from their deposits. This value falls within the acceptable regulatory limit, implying judicious handling of liquidity. The skewness is negative (-0.0167) with minimal spread (standard deviation = 5.80). Nevertheless, the Jarque-Bera test statistic value (14.14; $p < 0.01$) reflects the presence of non-normal characteristics.

Finally, Bank Size—measured by the natural logarithm of total assets—has an average of 17.47 with a standard deviation of 0.83. It varies between 16.04 and 18.99, reflecting minimal size variation among the sampled banks. The distribution is nearly symmetrical (skewness = 0.0896), and Jarque-Bera test statistic (12.70; $p < 0.01$) suggests that the data are mildly skewed away from normality. These statistical properties highlight the necessity for the use of sound estimation procedures in future regression models to allow for valid inference.

Model Selection Tests

Table 2. Model Selection Tests

Test	Prob.	Result
Chow test	0.0589	Common Effect Model
Hausman Test	0.6009	Random Effect Model
Lagrange Multiplier Tests	0.2888	Random Effect Model

The panel model selection tests are given in Table 2. The Chow Test provides a p-value of 0.0589, which is slightly higher than the 5% critical value, suggesting that the fixed effect model is not appreciably better than the common effect model. That being said, the Hausman Test has a p-value of 0.6009 (> 0.05), suggesting that the random effects model has a better fit than the fixed effects model. Furthermore, the Lagrange Multiplier (LM) test also produces a p-value of 0.2888, which is further evidence in favor of the use of the random effects model over the common effect model. Based on these results, the random effect model is selected as the most fitting estimation technique for this study.

Regression Results

Table 3. Regression Results: The Impact of Digital Transformation on Credit Risk (NPL)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3,702	0,968	3,826	0,000
DIGITAL_INDEX	-0,500	0,260	-1,923	0,056
SIZE	-0,047	0,046	-1,011	0,313
CAR	0,009	0,017	0,537	0,592
ROA	0,052	0,101	0,519	0,605
KREDIT_GROWTH	-0,011	0,009	-1,211	0,227
CASA	-0,002	0,005	-0,278	0,782
PDB_RIIL	-0,027	0,043	-0,622	0,534

$$Y_{it} = 3.702097 - 0.500111 - 0.046539 + 0.008928 + 0.052323 - 0.011043 \\ - 0.001503 - 0.026539$$

Table 3 presents the regression of the impact of digital transformation on credit risk, as a proxy by Non-Performing Loans (NPL). The negative coefficient of the DIGITAL_INDEX (-0.500) is statistically significant at the 10% level (p = 0.056), indicating that digital transformation can decrease credit risk, though the result is not statistically significant at the conventional 5% level. This finding is in line with Hoque et al. (2024), which set that digital transformation reduces credit risk through improved operating efficiency. The remaining control variables, including SIZE, CAR, ROA, CREDIT_GROWTH, CASA, and GDP_RIIL, do not have statistically significant effects on NPL. This aligns with the suggestion that although digitalization is positive in terms of improved credit risk management, it does not work in a standalone manner against general macroeconomic or structural factors.

Table 4. Regression Results: The Impact of Digital Transformation on Insolvency Risk (Z-Score)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	54,791	12,562	4,362	0,000
DIGITAL_INDEX	0,817	3,368	0,243	0,809
SIZE	-0,281	0,597	-0,470	0,639
CAR	-0,126	0,215	-0,586	0,559
ROA	-0,492	1,302	-0,378	0,706

KREDIT_GROWTH	-0,195	0,119	-1,643	0,102
CASA	0,014	0,071	0,198	0,843
PDB_RIIL	-0,031	0,552	-0,057	0,955

$$Y_{it} = 54.79085 + 0.817084 - 0.280503 - 0.125831 - 0.492239 - 0.195195 + 0.013994 - 0.031328$$

Table 4 presents the regression output for insolvency risk using the Z-Score. The coefficient for DIGITAL_INDEX is positive (0.817) but statistically not significant (p = 0.809), which indicates that digital transformation does not have a significant impact on insolvency risk during the observed period. Similarly, no control variables are significant, including SIZE (p = 0.639), CAR (p = 0.559), and ROA (p = 0.706). Contrary to evidence by Fan et al. (2024), which observed that digitalization dampens systemic risk through operational efficiency. The insignificance in this case is due to the fact of the relatively low maturity of digital infrastructure in the Indonesian banking sector or limitations to quantify long-term consequences of risk stabilization.

Table 5. Regression Results: The Impact of Digital Transformation on Liquidity Risk (LDR)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	77,905	9,805	7,945	0,000
DIGITAL_INDEX	1,694	2,632	0,644	0,521
SIZE	0,520	0,466	1,114	0,267
CAR	0,026	0,168	0,157	0,875
ROA	-0,731	1,019	-0,717	0,474
KREDIT_GROWTH	-0,096	0,093	-1,033	0,303
CASA	0,030	0,055	0,553	0,581
PDB_RIIL	0,439	0,432	1,017	0,310

$$Y_{it} = 77.90520 + 1.694153 + 0.519505 + 0.026417 - 0.730849 - 0.095622 + 0.030412 + 0.438827$$

Test for the impact of digital transformation on liquidity risk, defined in terms of the Loan-to-Deposit Ratio (LDR). The coefficient of DIGITAL_INDEX is positive (1.694) but statistically insignificant (p = 0.521), which means that digital transformation does not have any statistically significant impact on liquidity risk. Control variables SIZE, CAR, ROA, CREDIT_GROWTH, and CASA also show no significant relationship with LDR. This finding is consistent with Hoque et al. (2024), which reported that it failed to identify a significant effect of digital transformation on liquidity risk. One probable explanation is that technology initiatives within banking care more about customer interface and automation rather than radically changing liquidity management procedures.

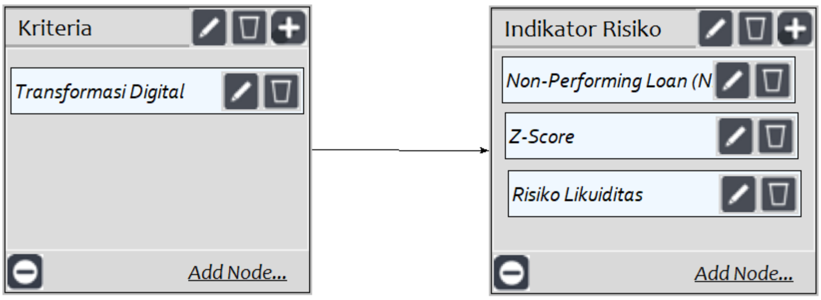

Figure 1. Analytical Hierarchy Process (AHP) Model Structure of Digital Transformation and Banking Risk Indicators

Figure 1 illustrates the hierarchical structure utilized in the Analytic Hierarchy Process (AHP) where Digital Transformation is set as the principal criterion that influences three critical indicators of risk: Non-Performing Loan (NPL), Z-Score (risk of insolvency), and Liquidity Risk. The format of the model gives the foundation for performing pairwise comparisons to determine the relative weights of each dimension of risk with respect to digital transformation initiatives for commercial banks.

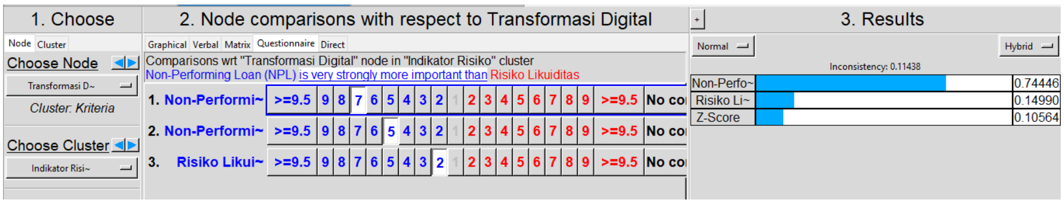

Figure 2. Pairwise Comparison Matrix: Risk Indicators in Relation to Digital Transformation

Figure 2 illustrates the pairwise comparison matrix utilized to rank the significance of the three indicators of risk relative to the digital transformation criterion. The results were as follows: NPL was considered far more significant relative to Liquidity Risk and moderately more significant relative to Z-Score. These qualitative evaluations are then transformed into quantitative scores through Saaty's AHP scale such that consistency testing can be performed and ultimate priority weights derived. The inconsistency index from the matrix is 0.1144, which is well within the normally accepted range of 0.10 to 0.15, and thus the pairwise comparisons are reasonably consistent (Lande et al., 2023).

Table 6. Priority Weights of Risk Indicators in the Context of Digital Transformation

Inconsistency		**0,1144**
Name	Normalized	Idealized
Non-Performing Loan (NPL)	0,7445	1,0000
Liquidity Risk	0,1499	0,2014
Z-Score	0,1056	0,1419

As revealed by Table 6, the AHP-generated priority weights also indicate that Credit Risk (NPL) has the highest normalized value of 0.7445, also idealized to 1.0000. This indicates that among the three dimensions, credit risk is the most critical area affected by digital transformation. Liquidity Risk ranks second at a normalized weightage of 0.1499 (idealized = 0.2014), while Z-Score (insolvency risk) is the least significant at a normalized weightage of 0.1056 (idealized = 0.1419). This suggests that stakeholders perceive digital transformation to have greatest impact on credit risk mitigation, followed by liquidity management, and least on insolvency measures.

Managerial Implications

The results show that digital transformation has the highest perceived impact on credit risk, as revealed through both regression and AHP outputs. This means that from the point of view of a bank manager, high consideration should be provided to making high-priority digital investments in the domains of credit evaluation, tracking loans, and early warning. Boosting digital expertise in these domains can help reduce non-performing loans and credit quality in general. Though no significant effects were identified on insolvency and liquidity risk, digital technologies can indirectly provide benefits in terms of enhanced reporting and real-time financial management. Banks are therefore required to adopt an extensive digital risk framework where technology deployment is synchronized with key risk priorities. Regulators such as OJK and Bank Indonesia can also apply these insights to policy by encouraging banks to integrate digital instruments into credit risk management processes in a way that allows digital transformation to not only enhance efficiency but also financial system stability.

CONCLUSION

This study aimed to examine the impact of digital transformation on risk-taking behavior for Indonesian commercial banks, in particular credit risk, insolvency risk, and liquidity risk. The findings indicate that digital transformation exerts a marginally significant negative impact on credit risk (NPL), demonstrating its potential to improve the quality of credit through improved data-monitoring and automation. However, there was no observed effect on insolvency risk (Z-score) or liquidity risk (LDR), suggesting that these risk dimensions are not influenced directly by digital programs or require longer time intervals to observe observable impacts. AHP analysis also validated the importance of credit risk, which was positioned as the most strongly focused risk dimension in the context of digital transformation. Thus, the study concludes that digital transformation is a primary force behind better risk governance, but its effect is greatest in credit risk management.

Recommendations

Banks are advised to align digital transformation programs to their risk management agenda, particularly to strengthen credit risk assessment and control frameworks. The focus needs to be on strengthening digital platforms for loan origination, monitoring, and recovery to contain NPLs effectively. Furthermore, to harvest the broader benefits of digitalization, banks are also recommended to invest in overall risk systems spanning liquidity and solvency aspects, although their short-term impacts are not statistically significant. Policymakers and regulators such as OJK and Bank Indonesia are called upon to develop targeted incentive and guideline frameworks that encourage responsible digital adoption, especially in credit activities. Further studies are recommended to explore the long-term influence of digital transformation across different risk categories as well as to examine the moderating role of institutional capacity and regulatory support.

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