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The Influence of Digital Transformation on Risk-Taking in Commercial Banks in Indonesia Using Text Mining

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ABSTRACT

This research examines the impact of digital transformation on banking risks, specifically focusing on credit risk (NPL), liquidity risk (LDR), and insolvency risk (Z-score). Employing a quantitative method, the study constructs a digital transformation index using text-mining techniques applied to annual reports of Indonesian commercial banks. The analysis utilizes Ordinary Least Squares (OLS), Fixed Effects (FE), and the System Generalized Method of Moments (SYS-GMM) on a dataset comprising 59 commercial banks in Indonesia from 2018 to 2024. The results reveal that digital transformation significantly raises credit risk. In contrast, its effects on liquidity and insolvency risks are statistically insignificant, suggesting potential improvements in credit evaluation through the use of enhanced data and technological tools. Additionally, the study demonstrates the utility of the SYS-GMM model in addressing endogeneity concerns in dynamic panel data. These findings can help regulators understand the strategic role of digital implementation and innovation in enhancing risk management and financial stability within the commercial banking sector.

KEYWORDS *Digital transformation, banking risk management, text-mining, SYS-GMM*

INTRODUCTION

Digital transformation is a vital strategy implemented by commercial banks to respond to changes in consumer behavior through the integration of financial services provided by financial sector businesses, known as Financial Technology (*FinTech*). *FinTech* is defined as financial innovation supported by technology, which can produce new business models, applications, processes, or products with a significant impact on financial markets, financial institutions, and the provision of financial services (Financial Stability Board, 2016). The implementation of a digital transformation strategy offers banks numerous benefits, including increased cost efficiency, enhanced profits, expanded business scale, and optimized organizational performance (Ayadi et al., 2025; Porfirio et al., 2024).

The disruption experienced by commercial banks caused by financial technology innovations has changed traditional banking business practices, which is an implication of the acceleration of digital transformation (Li C., et al., 2022). However, changes in business models that occur due to digital transformation can increase the risks that are inherent in the banking sector and give rise to new types of risks caused by disruption from the digital transformation process (Li C., et al., 2022). In addition, the impact of the disruption of the shift from a traditional bank model to a digital one hinders the operational movement of commercial banks in general and has the potential to disrupt the stability of the financial sector in Indonesia. The total assets of commercial banks relative to the total assets of the financial sector in Indonesia as of September 2024 were 78.209%, which means that if bank stability is disrupted due to the impact of digital transformation, the entire financial sector in Indonesia will be disrupted (CEIC Data, 2024).

The growth of digital transactions in Indonesia in 2023 was 215.3% compared to 2019. Furthermore, the total transaction volume in 2023 was 20.4 billion transactions, up 189.3% from 7.1 billion transactions in 2019 (Bank Indonesia, 2024). In addition to the COVID-19 pandemic, which was a factor in the digital transformation of banking in Indonesia (Li C., et al., 2022), one of the factors that supports the growth of digital transactions in Indonesia is the launch of the digital payment tool Quick Response Code Indonesia Standard (*QRIS*) on August 17, 2019, by Bank Indonesia. In April 2024, the nominal value of digital transactions via *QRIS* increased by 194.06% compared to April 2023, with a total of 48.9 million users and 31.86 million merchants (Indonesia.go.id, 2024).

The growth of digital transactions in Indonesia has been responded to by commercial banks through reducing the number of offices by 22% from 31,127 offices in 2019 to 24,276 offices in 2024 (*Otoritas Jasa Keuangan*, 2023). *Otoritas Jasa Keuangan* (*OJK*), as a financial services authority, has also responded to the digital transformation by issuing the Banking Digital Transformation Blueprint to accelerate the digital transformation of banking in Indonesia. The focus emphasized in the Banking Digital Transformation Blueprint has five main elements: Data, Technology, Risk Management, Collaboration, and Institutional Order, which aim to address the digital transformation of banking in Indonesia by balancing prudential aspects so that in its digital implementation and innovation, banks remain cautious about the challenges that will arise in the future (*Otoritas Jasa Keuangan*, 2021).

Several studies that have been conducted on the influence of innovation and implementation of digital transformation in the banking sector on the level of risk show mixed results (Wu, et al., 2023). One example of research on the impact of digital transformation on risk is measured using the level of non-performing loans (NPL), namely that bank products in the form of loan services collaborated with technological advances will reduce the impact of consumer defaults caused by information asymmetry between banks and borrowers by integrating data and information about prospective borrowers (Gomber, et al., 2017). Other studies show that the development of financial technology or *Fintech* using the internet shows a positive relationship with commercial bank risk. Research on the influence of technological developments uses measurements of the level of risk-taking: Non-Performing Loans (NPL) showing a positive relationship, Capital Adequacy Ratio (CAR) showing a positive relationship, and liquidity levels showing a negative relationship (Dong, et al., 2020). However, other studies show non-linear results, namely a U-shaped relationship, where there is a maximum turning point that can be used as a threshold for making crucial decisions in risk management (Chen et al., 2022; Guo & Shen, 2016; Wang et al., 2020).

Research on the impact of digital transformation has been widely conducted, but the results found are still very diverse due to the use of generalized risk variables. While in reference journals, risk calculations are adjusted to the type of risk to eliminate the generalization factor. Based on the results obtained, empirical testing should continue to be carried out for various types of risks. This study will only use credit risk, liquidity risk, and insolvency risk as dependent variables due to the complexity of quantifying operational risk and legal risk (Financial Stability Board, 2017; Vučinić, 2020). In addition, measurements for the three risks are carried out individually to avoid generalization in determining the risks experienced due to digital transformation. Furthermore, as a dependent variable, the implementation and innovation of digital transformation uses the text mining method in constructing the digital transformation index value from the annual financial reports of commercial banks. However, previous studies mostly used the index created by the Peking University Digital Financial Inclusion Index of China (*PKU_DFIIC*) or an index derived from public information compiled through search engines on the internet that may be influenced by sentiment from the media or regional aspects. Therefore, in this study, the digital transformation index from the annual financial reports of commercial banks was used and quantified because it was considered objective enough to describe digital transformation (Wu, et al., 2023).

RESEARCH METHOD

Building on the research model in Figure 1 proposed by Wu et al. (2023), this study attempts to analyze the impact of digital transformation implementation and innovation on risk in the commercial banking sector in Indonesia. In this study, a test will be conducted on the influence of digital transformation implementation and innovation on several types of bank risks, namely credit risk, liquidity risk, and insolvency risk, where the risk calculations are adjusted to the type of risk to eliminate the generalization factor.

The following is the equation model that will be used based on (Wu, et al, 2023):

$$Risk_{i,t} = \alpha \times Risk_{i,t-1} + \beta \times Fintech_{i,t-1} + \sum_{j=1}^{8} \gamma_j \times C_{j,i,t} + cons + \varepsilon \quad (3.1)$$

The following is an explanation of equation (3.1):

$Risk_{i,t}$: Credit Risk, Liquidity Risk and Insolvency Risk for Commercial Bank i year t.

$Fintech_{i,t-1}$: Lag of Digital transformation implementation and innovation index synthesized from keyword frequencies in Bank's annual financial reports.

$C_{j,i,t}$: Variable Control.

$cons$: Constant.

ε : Error.

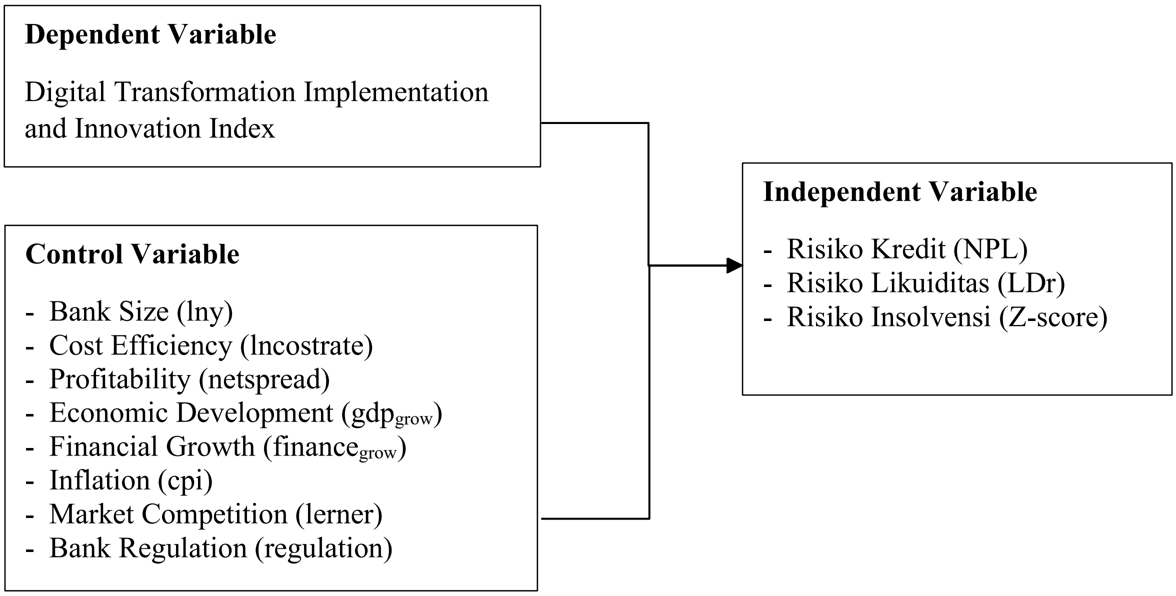

Figure 1 Research Model (Wu et al., 2023)

This research on the influence of implementation and technological innovation on risk-taking uses a quantitative approach. The quantitative approach will analyze the relationship between variables so that they can be analyzed using statistical procedures (Creswell, 2014). This research will use statistical methods with several different models, namely the Ordinary Least Squares (OLS), Fixed-Effect (FE), and System Generalized Method of Moments (SYS-GMM) regression models. The main model of this research uses the SYS-GMM model to ensure that the regression model used can handle endogeneity, autocorrelation, and heteroscedasticity (Arellano & Bond, 1991).

Data

This study uses data from commercial banks in Indonesia based on Indonesian banking statistics as of April 2024. The banks included consist of state-owned commercial banks and private commercial banks. Due to the limited availability of English language financial report data on public channels, the data used is only from 59 banks in the data collection period for 7 years, namely from 2018 to 2024.

The digital implementation and innovation claim index is obtained by synthesizing the bank's annual financial reports using text mining. The bank's annual financial reports are obtained through the respective bank's websites or through the Financial Services Authority website. The financial reports are then processed using text-mining to obtain the number of each word included in the lexicon that has been defined in the Independent Variable section.

Furthermore, for the dependent variable and control variables, data obtained from the annual financial reports are used. Several variables such as the Z-score and Lerner index are subjected to additional processing according to the equations explained in each variable. In addition, for the regulation variable, data is used from the List of Commercial and Sharia Bank Head Offices from the Financial Services Authority website.

All of these data form panel data for the last 7 years due to the limitations of the English language annual financial report data. Furthermore, after the data has been prepared, it will be processed using the OLS, FE, and SYS-GMM regression methods.

Hypothesis

Capital Adequacy Ratio (CAR), Non-Performing Loan (NPL), Return on Assets (ROA), and Loan to Deposit Ratio (LDR) are important indicators used by *OJK* to measure the performance of commercial banks in Indonesia. These indicators provide information on the level of credit risk (NPL), liquidity risk (LDR), and insolvency risk (CAR & ROA). In addition, to avoid generalization by using only one measure of risk, all three risk indicators are used. Therefore, the measurement of bank risk used in this hypothesis is credit risk, liquidity risk, and insolvency risk.

One of the businesses in the bank, namely providing loans to customers, has an inherent risk in the form of credit risk (Naili & Lahrichi, 2020). Implementation and innovation of digital transformation can affect the lending business, thus having a significant impact on credit risk in commercial banks. Technological developments such as Big Data and artificial intelligence are useful for reducing the operational costs of this credit business. Big Data and artificial intelligence can help analyze customer credit acquisition by collecting and processing credit information. The credit assessment process using technology will create a lower threshold for personal businesses and Micro, Small and Medium Enterprises (MSMEs) so that it will be easier to get credit approval and increase the scale of loan inclusiveness in banks (Ferrari, 2016; Guo & Zhu, 2022). However, the available Big Data is not yet comprehensive and accurate, so it can produce credit assessment models for customer loan applications that do not meet expectations.

Zhao et al. (2022) explained that the development of digital transformation in the banking sector will increase industrial competition, which will result in a decrease in bank profits and asset quality. One of the forms carried out by banks is to transform into digital banks (Jin et al., 2020). This transformation will result in banks being unable to increase their loan amounts, and income from credit interest will decrease.

Based on previous explanations, competition arising from digital transformation can cause banks to experience limitations in distributing loans, so that income from credit interest decreases. To overcome this, banks may increase loan interest rates (Huljak et al., 2022). However, this increase in interest rates has the potential to increase credit risk because it can affect the borrower's ability to meet their payment obligations. Therefore, the first hypothesis is as follows:

H1. Implementation and innovation of digital transformation have a positive relationship with commercial bank credit risk.

Liquidity risk arises from the mismatch between bank assets and liabilities (Liao & Yang, 2008). The development of financial technology accelerates financial disintermediation and reduces the cost of searching and switching for bank customers (Feyen et al., 2021; Thakor, 2020). As a result, commercial banks respond to increasingly fierce business competition. The bank's reaction changes the quality of assets and liabilities, which changes liquidity. Some digital banking companies use interest rates and payment facilities to divert deposits that would otherwise flow to banks for liability business (Li G., et al., 2022; Navaretti, et al., 2018). Amidst the increasing high funding costs for banks and the decline in the portion of individual deposits with low interest rates, deposit competition has led to a decline in deposit stability and asset quality of commercial banks (Dong, et al., 2020; Hu, et al., 2019; Zhao, et al., 2022). Commercial banks, in turn, sell various types of deposits through internet platforms. Profit sensitivity and customer attrition make this product different from conventional deposits (Liu C., 2021).

Furthermore, competition with financial technology-based financial companies causes commercial banks to lose their customers (Zhao & Xue, 2019). To remain competitive, digital banks adopt new business models that change their lending structure. This competition encourages increased credit for sectors that fall into the lower segment category (Zhan et al., 2018). However, as a result, the approved credit threshold becomes lower, so banks must increase loan loss provisions as a form of credit risk mitigation based on regulatory provisions. This ultimately has an impact on decreasing bank liquidity. As a result, the second hypothesis is obtained, which explains that:

H2. Implementation and innovation of digital transformation have a positive relationship with commercial bank liquidity risk.

In general, insolvency risk is considered a measure of a bank's overall risk-taking. Commercial banks can develop new financial products and enhance financial service channels with digital banks (Navaretti, et al., 2018). This will reduce fixed and variable costs and improve bank efficiency (Lee, et al., 2021; Wang, et al., 2021). As a result, the overall risk taken by banks will be reduced. Digital asset management, internet, and cloud computing reduce the fixed costs of commercial banks (Boot, 2016; Qi, et al., 2022; Varian, et al., 2010). With channel virtualization and service digitalization, geographical barriers in banking can be eliminated, which means lower fixed costs for building bank branches.

Although digital transformation increases credit risk and liquidity risk due to competition with other financial companies, technology investment in banks, such as real-time monitoring and artificial intelligence (AI), can improve bank management efficiency by reducing costs and optimizing organizational structures (Cheng & Qu, 2020; Guo & Shen, 2015; Liu & Jiang, 2021). In addition, digital banks support service diversification and improve the accuracy of banking product development and pricing (Li C., et al., 2022). Thus, commercial banks have the potential to achieve higher profitability, which contributes to increased stability and reduced insolvency risk. Thus, the third hypothesis is obtained as follows:

H3. The implementation and innovation of *FinTech* banks have a negative relationship with the insolvency risk of commercial banks.

Variables

This study examines three dependent variables representing bank risks: credit risk, measured by the non-performing loan (NPL) ratio; liquidity risk, measured by the natural logarithm of the loan-to-deposit ratio (LDR); and insolvency risk, measured by the logarithm of the Z-score. The independent variable is a Digital Bank (*Fintech*) Index, constructed through text mining of commercial banks' annual reports using a comprehensive, self-generated financial technology lexicon that encompasses both technological and business conceptual definitions derived from current literature and practices. Table 1 shows the keywords. Next, the researchers used Python to review textual information from banks' annual financial reports and calculate keyword frequencies. Finally, they calculated keyword frequencies by counting the number of keywords as a proportion of the number of words in the annual financial reports.

Table 1. Initial lexicon for the bank FinTech index. (Wu et al., 2023)

Subindex		Lexicon
Technology	Information Technology	Informatization Construction, Information Science, IT Governance, IT Architecture, Online, Quick Response Code, Opening, Informatization, Automation, Digitalization, Intelligent, Scene, Instant Messaging, 5G, Information System, Information Security, Open, Interconnect, sharing, Virtual Reality, Cyber-Physical Systems, FinTech, Financial Technology
	Artificial Intelligence	Artificial Intelligence, Face Recognition, Realtime Monitoring, Fingerprint Identification, Deep Learning, Wearable, Intelligence, Smart, Machine Learning, Face Swiping, Voiceprint, Intelligent Speech, Biometric Identification, Biometric Authentication, Text Mining, Brain-inspired Computing, Image Understanding, Natural Language Processing
	Blockchain Technology	Blockchain, Alliance Chain, Secure Multi-Party Computation, Distributed Computation
	Cloud Technology	Cloud Computing, Cloud Serving, Finance Cloud, Cloud Computing Architecture, IaaS, PaaS, SaaS
	Data Technology	Big Data, Data Mining, Data Stream, Data Set, Information Mining, CRM
	Internet Technology	Internet, Cellphone, Mobile, Mobile Device, Network, Remote, Electronic, API, Internet of Things, Mobile Communications
Business	Business (Service) Channels	Internet Finance, Biosphere, Open Banking, Online Banking, Electronic Banking, E-banking, Internet Banking, Mobile Banking, Electronic Wallet, WeChat

		Banking, Self-service Equipment, E-finance, Smart Banking, Online Financial Products, VTM, Electronic Commerce, E-commerce, Open Internet Banking, Open System Interconnection, Digital Banking, Online Supply Chain, Intelligent Retail, Contactless commerce, Scene Finance
	Gross Settlement	Third Party Payment, Mobile Payment, Online Payment, Net Payment, Mobile Phone and Payment, NFC Payment, Digital Currency, Electronic Payment, Barcode Payment, Two-dimensional Barcode Payment, EB-class Storage, Wearable Payment, Senseless Payment
	Resources Allocation	Internet Financing, Peer-to-peer Lending, P2P Lending, Crowdfunding, Internet lending, Network Financing, Online Investment, Equity-based Crowdfunding, Investment decision aid system, Online Financing, Financial Inclusion, Personalized Pricing, Scene Financing
	Financial Management	Consumer Finance, Online Wealth Management, Online Wealth Management, Online Insurance, Robot financing, Expert Advisor, Intelligent Advisor
	Risk Management	Big Data Credit, Big Data Risk Control

Control Variables

Control variables are variables used to capture the influence of other factors that are not the main focus of the study but can affect the dependent variable (Gujarati & Porter, 2009). With the presence of control variables, the regression model can provide more accurate and reliable estimates, especially in complex financial research, where many factors can affect the variables studied. Table 2 explains the control variables contained in this study, namely, the control variables that use bank-level and macro-level perspectives

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Table 2. Control Variables

Variable	Notation	Description
Bank Size	lny	Natural logarithm of total bank assets.
Cost Efficiency	lncostrate	Natural logarithm of cost-to-income ratio.
Profitability	netspread	Net interest spread.
Economic Development	gdp_{grow}	First-order difference of Natural logarithm of GDP.

Financial Growth	$finance_{grow}$	Deposit growth rate and loan scale.
Inflation	cpi	Consumer Price Index.
Market Competition	lerner	Lerner index.
Bank Regulation	regulation	Number of new banks established.

RESULT AND DISCUSSION

Descriptive Statistics

This study uses three dependent variable measures, namely Credit Risk (NPL), Liquidity Risk (lnLDr), and Insolvency Ratio (Z-score). Furthermore, for the independent variables, the researcher uses the Innovation Claim Index and Digital Transformation Implementation (Fintech) variables. As well as eight control variables, namely Total Bank Assets, Cost Efficiency, Profitability, State Economic Growth, Financial Growth, Inflation Rate, Market Competence, and Bank Regulation.

The variable L.Fintech, which is the first-order lag of the fintech index, has a mean of 0.0015 and a standard deviation of 0.0008. The very small value indicates that the level of bank involvement with digital transformation in the previous period was still limited. Very small value scales and narrow distributions can cause problems in linearity. Therefore, in the estimation model, a logarithmic transformation is performed on this variable to increase variation and improve model reliability (Wooldridge, 2013).

This natural logarithmic transformation will reduce the observation value to 353 data points because there is a minimum value of 0 as well as 1 data point. Table 3 is the data change that has been adjusted by the logarithmic transformation, with the number of observations that have been reduced.

Table 3. Descriptive Statistics

	Observation	Mean	S.D.	Max	Min
NPL_r	353	0,0303	0,0241	0,2590	0
lnLDr	353	-0,2046	0,6014	1,6214	-6,6454
Z-Score	353	3,7769	1,0707	7,0380	-0,0673
lnL.Fintech	353	-6,6168	0,6447	-4,9908	-11,6992
lny	353	31,2114	1,5924	35,4255	27,2964
lcostrate	353	-0,1100	0,2807	1,4549	-0,8747
netspread	353	0,0481	0,0462	0,6980	-0,0207
gdp_{grow}	353	0,0367	0,0262	0,0531	-0,0207
$finance_{grow}$	353	0,0792	0,0233	0,1120	0,0500
cpi	353	0,0266	0,0135	0,0551	0,0157
lerner	353	0,5265	0,0455	0,6012	0,4697
regulation	353	-1,6572	1,5910	0	-5

Variance Inflation Factor (VIF)

The main model, namely SYS-GMM, cannot be used if there is multicollinearity between the independent variables. In the OLS and FEM models, multicollinearity will cause the estimation to be unstable. In the SYS-GMM model, the existence of multicollinearity will cause overidentification problems and reduce the strength of the instrument (Roodman, 2009). Therefore, this test is carried out first before the explanation for each dependent variable is provided. Multicollinearity testing was conducted using VIF on all independent variables, including control variables.

Table 4. Variance Inflation Factor (VIF)

Variable	VIF
L.Fintech	1,151779
lny	1,292731
lcostrate	1,197182
netspread	1,041169
gdp_{grow}	5,657705
$finance_{grow}$	4,730006
cpi	3,030895
lerner	10,281344
regulation	3,175881
average	3,506521

The calculation results of the Variance Inflation Factor (VIF) in Table 4 show that the average value of VIF for the independent and control variables is 3.50621. Generally, a variable is considered to have multicollinearity if the average VIF> 10 (Gujarati & Porter, 2009). Therefore, the independent and control variables are considered to pass the multicollinearity test so that the SYS-GMM model can be carried out.

The Relationship between the Digital Implementation and Innovation Index and Credit Risk

Table 5 is the result of the classical assumption test, including the multicollinearity test, namely the normality test, heteroscedasticity test, and autocorrelation test. Based on the explanation from Table 5, it is obtained that both models have a non-normal distribution with a p-value of 0. This indicates that the residual model is not normally distributed and will affect confidence in the significance test of the model in the OLS model. However, in the FEM model with a significant amount of panel data, normal distribution is not a serious problem (Wooldridge, 2013).

The heteroscedasticity test for both models did not find any heteroscedasticity. Furthermore, for the autocorrelation test, positive autocorrelation was found in the residuals of the OLS model, which caused the OLS assumption to fail, and the OLS model could not be used. Based on the classical assumption test, it can be concluded that the OLS model cannot be used to explain the relationship between the dependent variable and the independent variable, and the FEM model can be used.

Based on the tests conducted on the SYS-GMM model in Table 6, it was found that the autocorrelation test was not significant, meaning that no second-order autocorrelation was found, so that the dynamic model was valid. In addition, the instrument test was also valid because the Hansen Test was not significant. Therefore, the SYS-GMM model can be used to explain credit risk variables.

Table 5. Classic Assumption Test of NPL vs Fintech OLS and FEM models

Classic Assumption Test	OLS		FEM	
	Result	Interpretation	Result	Interpretation
Normality Test (*p-value*)	0	Not normally distributed	0	Not normally distributed
Heteroscedasticity test (*p-value*)	0,3017	Homoscedasticity	0,3017	Homoscedasticity
Autocolleration test (DW)	1,22	Positive autocolleration	1,98	No Autocolleration

Table 6. Credit Risk Regression Test Results

	NPL_r OLS	NPL_r FE	NPL_r SYS-GMM
$LNPL_r$			0,0659
			(0,0415)
L.Fintech	-0,0034	-0,0014	0,0226**
	(0,002)	(0,0026)	(0,0111)
lny	0,0002	-0,0037	-0,0035
	(0,001)	(0,0039)	(0,0021)
lcostrate	0,0200	0,0094	0,0139
	(0,005)	(0,0059)	(0,0143)
netspread	0,0170	-0,0156	-0,0146
	(0,028)	(0,0304)	(0,0501)
gdp_{grow}	-0,1081	-0,1059	-0,1937*
	(0,113)	(0,0926)	(0,1075)
$finance_{grow}$	-0,0537	-0,0579	-0,0935
	(0,116)	(0,0939)	(0,1428)
cpi	-0,0104	-0,0422	-0,1360
	(0,161)	(0,1308)	(0,1504)
lerner	0,0228	0,0335	0,0653
	(0,088)	(0,0711)	(0,0957)
regulation	-0,0015	-0,0015	-0,0032**
	(0,001)	(0,0012)	(0,0013)
N	353	353	353
R^2	0,08	0,06	
AR (2)			0,173
Hansen			0,302

Significance Test *, **, *** are significance levels of 0.1; 0.05; and 0.01

Furthermore, the FEM model does show better results in terms of validity assumptions that result in a negative correlation with credit risk with no significance, but based on Table 6, it is obtained that the R^2 value is 6% which is relatively low, indicating that there are limitations in explaining NPL variability. In other studies, examining NPL using the digital transformation index using the FEM model, the R^2 value was obtained at 32.2% (Wu et al., 2023).

The SYS-GMM model in Table 6 shows that there are several significant variables that explain the NPL variable at 5% and 10% significance. The economic growth control variable has a significant test value of 10%, which is represented by the GDP growth variable. This variable shows a negative correlation with the NPL variable with a coefficient value of -0.1937. This means that when economic growth increases by 1 percent, the NPL ratio is expected to decrease by 0.1937 points,

Next are the L.Fintech and regulation variables, which are significant at the 5% level. The independent variable of the digital transformation implementation and innovation claim index represented by the L.Fintech variable shows a positive relationship with the NPL variable, with a coefficient value of 0.0226. This shows that when L.Fintech increases by 1 percent in logarithms, the NPL ratio is expected to increase by 0.0226. The banking regulation control variable in Indonesia, which is represented by the growth in the number of banks, shows a negative relationship with the NPL variable, with a coefficient value of -0.0032. This shows that when regulation increases by 1 percent in logarithms, the NPL ratio is expected to decrease by 0.0032.

The Relationship between the Digital Implementation and Innovation Index with Liquidity Risk

The heteroscedasticity test according to Table 7 for both OLS and FEM models, heteroscedasticity was found which can be interpreted that the variance values for both models are dynamic and require additional handling, thus violating the assumption test for both models. Furthermore, for the autocorrelation test, positive autocorrelation was found in the residuals of the OLS model, which caused the OLS assumption to fail, and the OLS model could not be used. However, in the FEM model using transformation to eliminate inter-individual variability, it often produces residuals that are freer from serial correlation (Wooldridge, 2013). Based on the classical assumption test, it can be concluded that the OLS and FEM models cannot be used to explain the relationship between the dependent variable and the liquidity risk variable.

Based on the tests conducted on the SYS-GMM model in Table 8, it was found that the autocorrelation test was not significant, meaning that no second-order autocorrelation was found, so that the dynamic model was valid. In addition, the instrument test was also valid because the Hansen Test was not significant. Therefore, the SYS-GMM model can be used to explain credit risk variables.

The SYS-GMM model in Table 8 shows that there are several significant variables that explain the LDR variable at 1% and 5% significance. The first-order lag variable LDR shows a positive and significant coefficient value of 0.3973 ($p < 0.01$), indicating persistence in liquidity risk, which means that the bank's liquidity conditions in the previous period still affect the current period's conditions. This reflects that liquidity risk management is not instantaneous and requires adjustment time.

Tabel 7. Classic Assumption Test of lnLDR vs Fintech OLS and FEM models

Classic Assumption Test	OLS		FEM	
	Result	Interpretation	Result	Interpretation
Normality Test (*p-value*)	0	Not normally distributed	0	Not normally distributed
Heteroscedasticity test (*p-value*)	0,0452	Heteroscedasticity	0,0452	Heteroscedasticity
Autocolleration test (DW)	1,16	Positive autocolleration	1,95	No Autocolleration

Table 8. Liquidity Risk Regression Test Results

	lnLDR OLS	lnLDR FE	lnLDR SYS-GMM
L lnLDR			0,3973***
			(0,0288)
L.Fintech	-0,0286	-0,0026	-1,0163
	(0,052)	(0,0707)	(0,8223)
lny	0,0166	0,3306***	0,1210
	(0,022)	(0,1048)	(0,1060)
lcostrate	-0,1397	0,0419	0,1086
	(0,123)	(0,1586)	(0,0884)
netspread	1,4288	0,4403	1,8274
	(0,695)	(0,8221)	(1,148)
gdp_{grow}	-1,2505	0,2012	3,0064
	(2,850)	(2,5041)	(2,491)
$finance_{grow}$	-2,7295	-2,6012	-1,409
	(2,930)	(6,8849)	(0,9457)
cpi	5,6477	3,5389*	7,5086**
	(4,055)	(3,5389)	(3,727)
lerner	-1,9276	-2,3762	-1,7631
	(2,214)	(1,9224)	(1,1653)
regulation	0,0190	-0,0090	0,0705
	(0,035)	(0,0321)	(0,0434)
N	353	353	353
R^2	0,06	0,10	
AR (2)			0,289
Hansen			0,279

Significance Test *, **, *** are significance levels of 0.1; 0.05; and 0.01

furthermore, the inflation control variable represented by the CPI shows a positive relationship with a coefficient value of 7.5086 and is significant at the 5% level. This shows that for every 1 unit increase in the logarithm of inflation, the bank's liquidity risk tends to increase by 7.51%, *ceteris paribus*.

The Relationship between the Digital Implementation and Innovation Index with Insolvency Risk

Table 9 is the result of the classical assumption test besides multicollinearity test, namely normality test, heteroscedasticity test and autocorrelation test. Based on the explanation from table 9, it is obtained that both models have non-normal distribution with p-value of 0. This indicates that the residual model is not normally distributed and will affect confidence in the significance test of the model in the OLS model.

However, in the FEM model with a significant amount of panel data, normal distribution is not a serious problem (Wooldridge, 2013). The heteroscedasticity test for both models found heteroscedasticity which can be interpreted that the variance value for both models is dynamic and requires additional handling so that it violates the assumption test for both models. Furthermore, for the autocorrelation test, positive autocorrelation was found in the residuals of the OLS and FEM models which caused the assumption to fail, and the OLS and FEM models could not be used.

Tabel 9. Classic Assumption Test of Z-score vs Fintech OLS and FEM models

Classic Assumption Test	OLS		FEM	
	Result	Interpretation	Result	Interpretation
Normality Test (*p-value*)	0,002	Not normally distributed	0	Not normally distributed
Heteroscedasticity test (*p-value*)	0,006	Heteroscedasticity	0,006	Heteroscedasticity
Autocolleration test (DW)	0,547	Positive autocolleration	1,364	Positive autocolleration

Based on the tests conducted on the SYS-GMM model in Table 10, it was found that the autocorrelation test was not significant, meaning that no second-order autocorrelation was found so that the dynamic model was valid. In addition, the instrument test was also valid because the Hansen Test was not significant. Therefore, the SYS-GMM model can be used to explain credit risk variables.

The SYS-GMM model in table 10 shows that there is only one significant variable that explains the insolvency risk variable at 5% significance, namely the LZ-score variable. The first-order lag variable Z-score shows a positive and significant coefficient value of 0.7608* (p <0.05), indicating persistence in insolvency risk, which means that the bank's insolvency conditions in the previous period still affect the current period's conditions. This reflects that overall bank stability has had a strong influence on the bank's stability conditions in the past. This shows that the influence of bank stability is not influenced simultaneously but from conditions in the previous time.

Table 10. Liquidity Risk Regression Test Results

	Z-score OLS	Z-score FE	Z-score SYS-GMM
L Z-score			0.7608**
			(0.4115)

L.Fintech	0.2450**	-0.0038	-1.1470
	(0.087)	(0.0406)	(0.7777)
lny	-0.0615*	-0.2212***	0.1186
	(0.037)	(0.0602)	(0.0980)
lcostrate	-1.5235***	-0.2697***	-0.3316
	(0.203)	(0.0912)	(0.5210)
netspread	-3.8846***	0.7105	-0.0805
	(1.154)	(0.4725)	(1.8354)
gdp_{grow}	-1.5199	0.8336	2.5342
	(4.732)	(1.4392)	(3.0190)
$finance_{grow}$	-2.4356	-2.5398*	1.3454
	(4.864)	(1.4592)	(2.6257)
cpi	-5.0992	-2.7080	4.5420
	(6.732)	(2.0339)	(5.0782)
lerner	3.6963	2.9049***	0.0454
	(3.676)	(1.1048)	(2.0019)
regulation	-0.0119	0.0511***	0.0336
	(0.058)	(0.0184)	(0.04272)
N	353	353	353
R^2	0,185	0,2482	
AR (2)			0,755
Hansen			0,907

Significance Test *, **, *** are significance levels of 0.1; 0.05; and 0.01

The hypothesis regarding the relationship between the implementation and innovation of digital transformation has a positive relationship with the credit risk of commercial banks is stated not to be rejected based on the significance of the relationship obtained from the results of data analysis. This finding aligns with Wu et al (2023), which suggests that digital transformation in commercial banking has led to an increase in credit risk. In addition, the results also align with the findings of Zhao et al. (2022), which indicate that the ease of providing loans increases credit risk. Providing credit without collateral, which is one of the current banking products to compete with online loan services, is one form of ease in providing loans in Indonesia. Therefore, OJK's support in the form of the Banking Digital Transformation Blueprint should be able to regulate strict regulations on credit risks caused by the digital transformation of commercial banks.

The control variables of economic growth and regulation play a role in explaining the NPL variable, exhibiting a negative relationship. This shows that an increase in GDP contributes to a decrease in NPL, because higher economic growth increases the debtor's payment capacity and strengthens financial stability and strict regulations, including higher capital requirements, encourage banks to be more careful in distributing credit, thereby reducing the risk of non-performing loans (Anita et al., 2022; Goyal et al., 2023). Considering control variables that can explain credit risk can provide a greater role for OJK and BI as regulators to oversee technological developments directly related to loan provision to debtors, especially digital banks, which facilitate quick application submission.

The hypothesis regarding the relationship between the implementation and innovation of digital transformation has a positive relationship with the liquidity risk of commercial banks is rejected because there is no significant relationship obtained from the results of data analysis. The L.Fintech variable is not significant in the SYS-GMM model, which means that the development of fintech has not had a relationship with banking liquidity during this analysis period. For liquidity risk, the regression results show that LDR has no significant relationship with L.FinTech. This indicates that the application of financial technology does not have a direct impact on the level of banking liquidity, or its impact may be more complex and influenced by other factors such as regulations and past bank liquidity risk conditions, which are in line with the significant value of the first-order LDR lag.

This finding differs from the main reference studies, Gu and Yang (2018) and Daud et al. (2021), which found that FinTech can increase liquidity risk by accelerating transactions and increasing the volatility of funds entering and leaving the banking system. Therefore, this difference could be caused by the characteristics of Banks in Indonesia according to PBI No.12/19/PBI/2010 concerning Giro Reserves Requirements, which regulates the LDR threshold value, which ranges from 78%-92% (*Bank Indonesia*, 2013). The LDR threshold becomes a disincentive for banks to be able to control their liquidity value so that they avoid liquidity risk due to disruption from technology implementation. Therefore, it causes liquidity risk to be less sensitive to technology, because banks focus more on maintaining liquidity balance than aggressive credit expansion using technology.

This finding also indicates that rising inflation can increase liquidity risk in banks represented in bank products for the financing market. In conditions of high inflation, operational and interest expenses on bank liabilities can increase, thereby increasing the possibility of a mismatch between funds collected and distributed—which ultimately increases liquidity risk. In addition, research by Hidayat (2023) on Bank Syariah Indonesia shows that inflation has a positive effect on liquidity risk, as measured by the Financing to Deposit Ratio (FDR).

The hypothesis regarding the relationship between the implementation and innovation of digital transformation has a negative relationship with the risk of commercial bank insolvency is rejected because there is no significant relationship obtained from the results of data analysis. This finding is different from the main reference research and Li C., et al., (2022) where the application of technology in commercial banks can obtain higher profitability, which in turn increases stability and reduces the risk of bankruptcy. However, this is in line with the findings in the research of Zhao et al., (2022) and Cevik (2023) which show that there is no significant relationship between digital transformation and banking stability. Based on this, banks have not optimally utilized fintech to strengthen their capital structure and risk management.

Implications

Based on the research findings indicating that technology implementation significantly increases credit risk, regulators are urged to strengthen oversight of digital credit products by developing technology-based risk governance guidelines and conducting periodic evaluations of digitalization's impact on asset quality, incorporating macroeconomic analyses. Banks must exercise greater caution by prioritizing enhanced risk scoring and credit underwriting systems through big data analytics to prevent rising NPLs from moral hazard, while also improving their technological capabilities with advanced stress testing mechanisms, especially since digital transformation has not yet significantly impacted funding structures or long-term stability. Theoretically, this study confirms the persistent role of risk management in shaping bank risks and supports previous findings that digital transformation enhances competition and borrower access—potentially increasing default risks—while also demonstrating that macroeconomic conditions significantly influence credit and liquidity risks, thereby providing a valuable foundation for future research on bank risk management in the digital era.

CONCLUSION

This study investigated the influence of digital transformation on risk-taking in Indonesian commercial banks, constructing a novel text-mining index from annual reports (2018-2024) and employing SYS-GMM methodology to address endogeneity. The results demonstrate that digital transformation significantly increases credit risk, supporting the hypothesis that easier access to digital lending introduces vulnerabilities in credit assessment, a finding aligned with moral hazard theory where reduced screening incentives lead to higher defaults. Conversely, digital transformation showed no significant impact on liquidity or insolvency risks, suggesting that existing regulatory frameworks effectively constrain liquidity management and that digital technologies have not yet fundamentally altered banks' core funding structures or long-term stability.

The study acknowledges several limitations, including its reliance on a declarative, claim-based index rather than quantitative investment or transaction data, a relatively short observation period that may not capture long-term effects, and a sample restricted to commercial banks, which limits generalizability to smaller rural banks or non-bank financial institutions. Future research is encouraged to incorporate variables such as implementation quality and regulatory effectiveness, utilize non-linear models or alternative estimation methods to examine long-term technological cycles, and develop a more context-appropriate lexicon for Indonesia. The ongoing support from the *Otoritas Jasa Keuangan* for digital transformation is expected to improve data availability, thereby strengthening the theoretical implications of future studies.

REFERENCES

Anita, S. S., Tasnova, N., & Nawar , N. (2022). Are non-performing loans sensitive to macroeconomic determinants? an empirical evidence from banking sector of SAARC countries. *Future Business Journal, 7*.

Ayadi, R., Chiaramonte, L., Cucinelli, D., & Migliavacca, M. (2025). Digitalization and banks' efficiency: Evidence from a European analysis. *International Review of Financial Analysis, 97*(103837).

Bank Indonesia. (2024). *Statistik Sistem Pembayaran dan Infrastruktur Pasar Keuangan (SPIP).* Jakarta: Bank Indonesia.

CEIC Data. (2024). *Indonesia Banks Assets to Financial Sector Assets.* United Kingdom: CEIC Data. Retrieved January 2025, from https://www.ceicdata.com/en/indonesia/financial-system-statistics-banking-sector/banks-assets-to-financial-sector-assets

Cevik, S. (2023). *The Dark Side of the Moon? Fintech and Financial Stability.* International Monetary Fund.

Chen, B., Yang, X., & Ma, Z. (2022). Fintech and Financial Risks of Systemically Important Commercial Banks in China: An Inverted U-Shaped Relationship. *Sustainability*, 14 (10).

Cheng, M., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal, 63*, 101398.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.).* Sage.

Daud, S., Ahmad, A., Khalid, A., & Azman-Saini, W. (2022). FinTech and financial stability: Threat or opportunity? *Finance Research Letters, 47*, 102667.

Dong, J., Yin, L., Liu, X., Hu, M., Li, X., & Liu, L. (2020). Impact of internet finance on the performance of commercial banks in China. *International Review of Financial Analysis*, 101579.

Ferrari, R. (2016). *FinTech Impact on Retail Banking - From a Universal Banking Model to Banking Verticalization.* (S. Chishti, & J. Barberis, Eds.) Chichester, UK: John Wiley & Sons, Ltd.

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., & Saal, M. (2021). Fintech and the digital transformation of financial services: implications for market structure and public policy. *BIS Paper*, 117.

Financial Stability Board. (2016). *FinTech: Describing the landscape and a framework for analysis.* Retrieved from https://www.fsb.org/wp-content/uploads/P140219.pdf.

Financial Stability Board. (2017). *Financial Stability Implications from FinTech.* Switzerland: Financial Stability Board. Retrieved from https://www.fsb.org/uploads/R270617.pdf

Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital Finance and FinTech: current research and future research directions. *Journal of Business Economics* , 537 - 580.

Goyal, S., Singhal, N., Mishra, N., & Verma , S. K. (2023). The impact of macroeconomic and institutional environment on NPL of developing and developed countries. *Future Business Journal, 45*.

Gu, H., & Yang, L. (2018). Internet Finance and Bank Risk Taking: Evidence Based on China’s Banking Industry. *World Economy, 41*, 75-100.

Gujarati, D., & Porter, D. (2009). *Basic Econometrics.* New York: McGraw Hill Inc.

Guo, L., & Zhu, K. (2022). Fintech, Bank Risks, and Business Performance: From the Perspective of Inclusive Finance. *China Economic Transition*, 242-261.

Guo, P., & Shen , Y. (2016). The impact of Internet finance on commercial banks’ risk taking: evidence from China. *China Finance and Economic Review*, 16.

Hidayat, M. (2023). The Effect of Economic Growth and Inflation on Liquidity in “Bank Syariah Indonesia". *Economics Studies and Banking Journal (DEMAND)*.

Hu, Z., Ding, S., Li, S., & Chen, L. (2019). Adoption Intention of Fintech Services for Bank Users: An Empirical Examination with an Extended Technology Acceptance Model. *Symmetry, 11*(3), 340.

Huljak, I., Martin, R., Moccero, D., & Pancaro, C. (2022). Do non-performing loans matter for bank lending and the business cycle in euro area countries? *Macroeconomics and Monetary Policy*, 1050-1080.

Indonesia.go.id. (2024, Juni 9). Transaksi Digital Tumbuh Pesat. Jakarta, Indonesia. Retrieved January 2025, from https://indonesia.go.id/kategori/editorial/8279/transaksi-digital-tumbuh-pesat?lang=1

Jin, H., Li, H., & Liu, Y. (2020). FinTech, Banking Risks and Market Crowding-out Effect. *Journal of Finance and Economics, 46*(5), 52-65.

Lee, C.-C., Li, X., Yu, C.-H., & Zhao, J. (2021). Does fintech innovation improve bank efficiency? Evidence from China's banking industry. *International Review of Economics & Finance, 74*, 468-483.

Li, C., He, S., Tian, Y., Sun, S., & Ning, L. (2022). Does the bank's FinTech innovation reduce its risk-taking? Evidence from China's banking industry. *Journal of Innovation & Knowledge, 7*(3), 100219.

Li, G., Elahi, E., & Zhao, L. (2022). Fintech, Bank Risk-Taking, and Risk-Warning for Commercial Banks in the Era of Digital Technology. *Frontiers in Psychology*, 934053.

Liao, M., & Yang, Y. (2008). On the liquidity risk management of commercial banks and supervisory challenges. *Journal of Financial Research*, 69-79.

Liu, C. (2021). FinTech and the reconstruction of banking value chain. *Financial Regulation Research*, 1-11.

Liu, M., & Jiang, W. (2021). Does FinTech Exacerbate or Reduce the Risk-Taking of Commercial Banks: Empirical Evidence from the Chinese Banking Industry. *Business Research*, 63-74.

Naili, M., & Lahrichi, Y. (2020). The determinants of banks' credit risk: Review of the literature and future research agenda. *International Journal of Finance & Economics, 27*(4), 334-360.

Navaretti, G., Calzolari, G., Mansilla-Fernandez, J., & Pozzolo, A. (2018). Fintech and Banking. Friends or Foes? *European Economy – Banks, Regulation, and the Real Sector, 2017.2*.

Otoritas Jasa Keuangan. (2021). *Cetak Biru Transformasi Digital Perbankan.* Jakarta: Otoritas Jasa Keuangan.

Otoritas Jasa Keuangan. (2023). *Statistik Perbankan Indonesia - Desember 2023.* Jakarta: Otoritas Jasa Keuangan. Retrieved from https://ojk.go.id/id/kanal/perbankan/data-dan-statistik/statistik-perbankan-indonesia/Pages/Statistik-Perbankan-Indonesia---Desember-2023.aspx

Porfirio, J. A., Felício, J., & Carrilho, T. (2024). Factors affecting digital transformation in banking. *Journal of Business Research, 171*(114393).

Qi, H., Yang, K., & Wang, W. (2022). Does FinTech change the market power of traditional banks in China? *Journal of Business Economics and Management, 23*(5), 1060-1083.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics, 71*(1), 135-158.

Thakor, A. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation, 41*, 100833.

Varian, H., Farrell, J., & Shapiro, C. (2010). *The Economics of Information Technology.* Cambridge University Press.

Vučinić, M. (2020). Fintech and Financial Stability Potential Influence of FinTech on Financial Stability, Risks and Benefits. *Journal of Central Banking Theory and Practice, 9*(2), 43 - 66.

Wang, R., Liu, J., & Luo, H. (2020). Fintech development and bank risk taking in China. *The European Journal of Finance* , 397 - 418.

Wang, Y., Xiuping, S., & Zhang, Q. (2021). Can fintech improve the efficiency of commercial banks? —An analysis based on big data. *Research in International Business and Finance, 55*, 101338.

Wooldridge, J. M. (2013). *Introductory Econometrics A Modern Approach* (5 ed.). South-Western, Mason.

Wu, X., Jin, T., Yang, K., & Qi, H. (2023). The impact of bank FinTech on commercial banks' risk-taking in China. *International Review of Financial Analysis*, 90,102944.

Zhan, M., Zhang, C., & Shen, J. (2018). Development of internet finance and the bank lending transmit channel of monetary policy. *Economic Research Journal, 53*(4), 63-76.

Zhao, J., Li, X., Yu, C.-H., Chen, S., & Lee, C.-C. (2022). Riding the FinTech innovation wave: FinTech, patents and bank performance. *Journal of International Money and Finance, 122*, 102552.