Latent structure of banking risk: An exploratory factor analysis of financial ratios in Indonesian commercial banks, 2021–2024

Prita Laura Antoneta Ratuliu
Corresponding e-mail: pritaratuliu09@gmail.com
Sam Ratulangi University - Indonesia

Diana Nova Lintong
Sam Ratulangi University - Indonesia

Abstract

Banking risks consist of various types of interrelated risks that must be managed in an integrated manner in accordance with the Enterprise Risk Management (ERM) framework. However, most previous studies have relied on regression approaches that test the relationships between variables separately, resulting in limited examination of the structural relationships among these risks. This study identifies the structure of banking risk factors based on the financial ratios of conventional commercial banks listed on the Indonesia Stock Exchange for the period 2021–2024. The study sample consists of 26 banks, selected using purposive sampling, yielding 104 firm-year observations; following the removal of one outlier observation, the final analysis was conducted on 103 observations. The study employed Exploratory Factor Analysis (EFA) on eight financial ratios, namely the Capital Adequacy Ratio (CAR), Loan-to-Deposit Ratio (LDR), Non-Performing Loan (NPL), Operating Expenses to Operating Income Ratio (BOPO), Net Open Position (PDN), Return on Assets (ROA), Return on Equity (ROE), and Net Interest Margin (NIM). The results, based on the final 103-observation model, indicate that the data are suitable for analysis using EFA, with a KMO value of 0.712, a significant Bartlett's Test of Sphericity (Sig. = 0.000), and all MSA values ≥ 0.50. Based on the factor analysis results, two main factors emerged that explain 63.65% of the total data variance. The first factor is the Profitability-Efficiency-Credit Quality Factor, comprising BOPO, NPL, ROA, and ROE, which accounts for 39.39% of the variance. The second factor is the Capital-Liquidity-Market Risk Factor, comprising CAR, LDR, NIM, and PDN, which accounts for 24.26% of the variance. The most dominant indicator in the first factor is BOPO, with a rotated loading of −0.937, while in the second factor it is CAR, with a rotated loading of 0.808.

Keywords: banking risk; enterprise risk management; exploratory factor analysis; financial ratios

Received
1 July 2026

Revised
9 September 2026

Accepted
10 September 2026

Published
11 September 2026

DOI: 10.58784/ramp.473

Copyright © 2026 Prita Laura Antoneta Ratuliu, Diana Nova Lintong

This work is licensed under a Creative Commons Attribution 4.0 International License.

Introduction

The banking sector plays a strategic role in the economy as a financial intermediary institution that collects funds from the public and redistributes them in the form of credit to productive sectors. Banking stability is one of the main pillars in maintaining financial system stability and promoting economic growth. In carrying out its functions, banks face various types of risks, such as credit risk, liquidity risk, operational risk, market risk, and capital risk, which are interrelated. Therefore, risk management is an important factor in maintaining the sustainability of banking operations.

During the 2021–2024 period, the Indonesian banking sector experienced risk dynamics influenced by the post-COVID-19 economic recovery, global economic uncertainty, and increases in benchmark interest rates. These conditions increased pressure on asset quality, the cost of funds, and the potential increase in Non-Performing Loans (NPLs) due to the declining repayment capacity of borrowers. This indicates that banking risks are complex and interrelated (Rose & Hudgins, 2013).

The capital condition of banks is an important factor in maintaining banking stability. Capital adequacy is measured by the Capital Adequacy Ratio (CAR), which reflects a bank's ability to absorb potential losses arising from its operational activities. Banks with adequate CAR have greater capacity to withstand economic pressures and maintain the continuity of their operations (Saunders & Cornett, 2019).

Another risk that should be considered is liquidity risk, which is measured using the Loan-to-Deposit Ratio (LDR), indicating a bank's ability to channel third-party funds into loans. Market risk is measured by the Net Open Position (PDN), which reflects the difference between a bank's foreign currency assets and liabilities relative to its capital. Bank Indonesia sets the maximum Net Open Position at 20% of a bank's capital. Operational efficiency is measured using the Operating Expenses to Operating Income Ratio (BOPO), while profitability is measured using Return on Assets (ROA) and Return on Equity (ROE).

A bank's ability to generate profits, as reflected by ROA and ROE, is inseparable from the interest income earned through its intermediation activities. This income is generally measured using the Net Interest Margin (NIM), which measures a bank's ability to generate net interest income from its earning assets. The stability of the Indonesian banking sector remained relatively well maintained, with the capital adequacy ratio ranging from 25% to 27% and the non-performing loan ratio remaining under control. However, global economic uncertainty and changes in monetary policy require banks to continuously strengthen risk management through various financial ratios.

Previous studies in the banking sector have primarily focused on analyzing causal relationships among financial variables using regression approaches. Widyaningsih and Sampurno (2022) analyzed the effect of financial ratios on bank performance, while Rosadi and Ramadhan (2024) examined the effects of CAR, NPL, BOPO, LDR, and NIM on ROA using multiple linear regression. These studies indicate that financial ratios are used as indicators for assessing bank soundness, covering aspects of capital, credit risk, liquidity, profitability, and operational efficiency. However, regression approaches only explain the partial effects among variables and are not able to reveal the latent structure, namely the risk factors that cannot be directly observed but are reflected through the relationships among financial ratios. Therefore, this study employs Exploratory Factor Analysis (EFA) to identify the structure of banking risk factors based on the relationships among financial ratios, thereby providing a more comprehensive description of the dimensions of banking risk.

This study uses Exploratory Factor Analysis (EFA) to identify the structure of banking risk factors by grouping various financial ratios into several major factors. The analysis is conducted using BOPO, CAR, LDR, NPL, PDN, ROA, ROE, and NIM of conventional commercial banks in Indonesia, thereby providing a more comprehensive description of the banking risk structure than an analysis of individual financial ratios. This study aims to identify the risk factors that are formed and determine the most dominant contributing indicators. Building on the six ERM-based risk dimensions discussed in Section 2 (capital, credit, liquidity, operational, profitability, and market risk), this study further examines the extent to which the empirically extracted factor structure corresponds to, or diverges from, this a priori six-dimension taxonomy. The findings are expected to provide useful input for banking risk management and the development of future research in the field of risk management.

Literature review

Enterprise Risk Management (ERM) theory

The Committee of Sponsoring Organizations of the Treadway Commission (COSO, 2017) defines Enterprise Risk Management (ERM) as a process involving the board of directors, management, and all organizational personnel to identify, manage, and control risks within the organization's risk appetite so that the company's objectives can be achieved. According to Fraser et al. (2021), ERM is an integrated approach that helps organizations deal with uncertainty by identifying, managing, and responding to risks comprehensively while determining the level of risk that can be accepted to optimize opportunities.

In this study, ERM is used as the theoretical foundation for identifying and classifying the structure of banking risk factors through factor analysis of financial ratios, thereby providing a more comprehensive description of the banking risk structure and supporting integrated risk management in achieving corporate objectives.

Banking risk

Risk is an inseparable part of banking activities. According to Bessis (2015), banking risk is the potential for losses arising from various decisions and operational activities of banks, such as lending, foreign exchange transactions, and other financial services. As financial service institutions, banks face risk characteristics that differ from those of manufacturing companies because the products they provide are intangible assets. Therefore, the ability of banks to identify, manage, and control risks is an important factor in maintaining their stability and operational sustainability.

In this study, banking risk is represented by six dimensions, namely credit risk, liquidity risk, operational risk, profitability risk, capital risk, and market risk. These six types of risk are interrelated and collectively reflect the soundness of banks; therefore, they need to be managed in an integrated manner in accordance with the principles of Enterprise Risk Management (ERM).

Financial ratios

Financial ratios are analytical tools used to assess a company's financial condition and performance by comparing items in the financial statements, thereby providing information about the company's financial condition (Kasmir, 2021). Several ratios commonly used to assess bank performance and banking risk are as follows:

a. Capital Adequacy Ratio (CAR)

According to Gina et al (2025) Capital Adequacy Ratio (CAR) is a ratio used to assess a bank’s capital adequacy in anticipating risks arising from the assets it holds.

CAR = (Bank Capital ÷ Risk-Weighted Assets) × 100%

b. Loan to Deposit Ratio (LDR)

The Loan-to-Deposit Ratio (LDR) is a ratio used to measure the proportion of loans extended by a bank relative to public deposits and the bank's own capital used to finance those loans (Kasmir, 2021).

LDR = (Total Loans ÷ Third-Party Funds) × 100%

c. Non-Performing Loan (NPL)

According to Yam (2023), the Non-Performing Loan (NPL) is a ratio used to assess bank performance from the perspective of business risk, particularly credit risk.

NPL = (Non-Performing Loans ÷ Total Loans) × 100%

d. Operating Expenses to Operating Income Ratio (BOPO)

According to Yulianto (2024), BOPO is a ratio used to measure a bank’s efficiency in managing operating expenses compared with operating income.

BOPO = (Operating Expenses ÷ Operating Income) × 100%

e. Net Open Position (PDN)

According to Harun et al. (2021), the Net Open Position (PDN) is the net difference (mismatch) between foreign currency assets and liabilities after taking off-balance-sheet accounts into consideration.

PDN = [(Foreign Currency Assets − Foreign Currency Liabilities) + Off-Balance-Sheet Position] ÷ Equity × 100%

f. Return on Assets (ROA)

Return on Assets (ROA) is a profitability ratio used to assess a company's ability to generate profits from all assets employed in its operational activities (Hartati, 2024).

ROA = (Profit before Tax ÷ Total Assets) × 100%

g. Return on Equity (ROE)

Hartati (2024) explains that Return on Equity (ROE) is a ratio that measures a company's ability to generate profits from shareholders' equity.

ROE = (Profit after Tax ÷ Total Equity) × 100%

h. Net Interest Margin (NIM)

Net Interest Margin (NIM) is a ratio that measures a bank's ability to generate net interest income from earning assets. A higher NIM indicates a better ability of the bank to generate interest income (Silitonga, 2022).

NIM = (Net Interest Income ÷ Average Earning Assets) × 100%

Factor analysis

Factor analysis was first introduced by Spearman (1904) through his research on the structure of mental ability. Lasiyono and Sulistiyawan (2024) explain that factor analysis is one of the multivariate analysis techniques used to reduce a number of correlated variables into several new factors. The objective of factor analysis is to explain the structure of relationships among variables so that the main dimensions obtained are simpler and easier to interpret.

Conceptual framework

Figure 1 presents the conceptual framework underlying this study. The eight candidate financial ratios (CAR, LDR, NPL, BOPO, PDN, ROA, ROE, and NIM) are hypothesized to reflect an underlying, unobserved banking-risk construct, which is theoretically decomposed into the six ERM-based risk dimensions described in Section 2.2 (capital, credit, liquidity, operational, profitability, and market risk). This framework is exploratory rather than confirmatory: Exploratory Factor Analysis (EFA) is used in Section 4 to empirically examine how the eight indicators actually group together, and the resulting factor structure is then compared against this a priori framework in the Discussion.

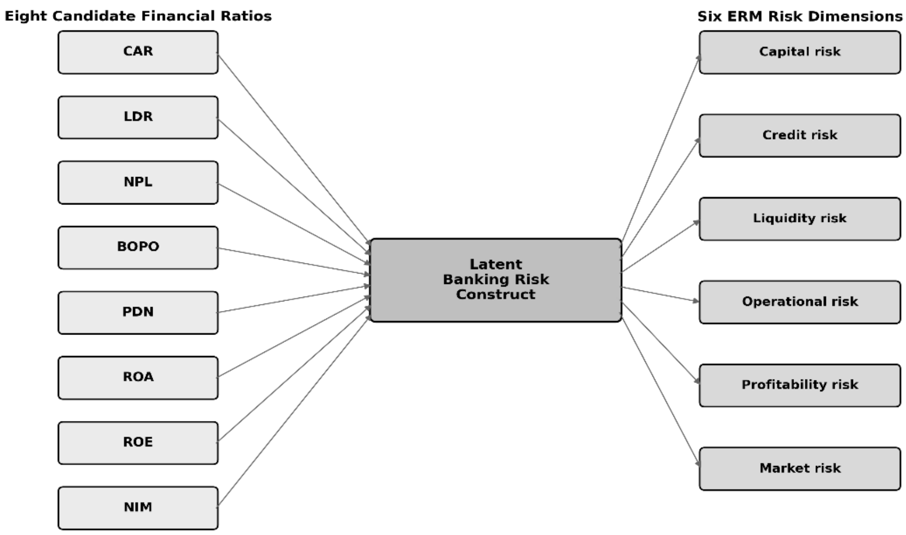

Figure 1. Conceptual framework

Source: Developed by the authors (2026), based on the eight financial ratios and the six ERM-based risk dimensions

Research method

This study employed a quantitative approach with a population of 47 conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2021-2024 period. The research sample was selected using a purposive sampling technique based on the criteria that the banks were continuously listed throughout the study period and had complete financial statement data. Based on these criteria, 26 banks were selected, resulting in a total of 104 firm-year observations. The data used in this study were secondary data obtained from annual financial statements published on the official website of the Indonesia Stock Exchange (www.idx.co.id) and the official websites of each bank.

The data were analyzed using Exploratory Factor Analysis (EFA) with the assistance of IBM SPSS. Factor extraction was performed on the correlation matrix (rather than the covariance matrix), the standard approach for EFA given the differing measurement scales of the eight ratios (Table 1). The analysis procedures included testing data suitability using the Kaiser–Meyer–Olkin (KMO) measure, Bartlett's Test of Sphericity, and the Measure of Sampling Adequacy (MSA), followed by factor extraction using Principal Component Analysis (PCA), determination of the number of factors based on eigenvalues greater than 1, factor rotation using the Varimax method, and factor interpretation based on factor loading values.

The interpretive thresholds applied in the Results section are as follows: a KMO value below 0.50 is considered unacceptable, 0.50–0.59 is "poor," 0.60–0.69 is "mediocre," 0.70–0.79 is "average," and 0.80 and above is "meritorious" (Kaiser, 1974); Bartlett's Test of Sphericity is considered significant at Sig. < 0.05; each variable's MSA value must be at least 0.50 to be retained; and a factor loading is considered to meaningfully define a factor when its absolute value exceeds 0.50.

Results and discussion

Results

Overview of the research object

The object of this study was conventional commercial banks listed on the Indonesia Stock Exchange (IDX) during the 2021–2024 period. Conventional commercial banks are banks that conduct their business activities in accordance with central bank policies and applicable laws and regulations.

Descriptive statistical analysis

Table 1. Descriptive statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
BOPO	104	41.70	287.86	81.9991	25.29578
CAR	104	17.49	169.92	36.0719	24.03418
LDR	104	32.68	163.19	87.4658	23.58236
NPL	104	0.01	9.08	2.8256	1.66147
PDN	104	0.00	9.78	1.2294	1.70344
ROA	104	0.08	14.75	1.8854	1.77650
ROE	104	0.21	95.44	9.7430	11.02951
NIM	104	2.22	10.45	5.0806	1.54263

Based on Table 1, this study used 104 observations prior to outlier removal. The descriptive statistical analysis indicates that the mean BOPO ratio was 81.9991%, suggesting that the banks generally maintained a relatively good level of operational efficiency, although the maximum value of 287.86% indicates the presence of a bank with very low operational efficiency. The mean CAR was

36.0719%, reflecting a strong capital position with relatively high variation, while the mean LDR of 87.4658% indicates that the banks' intermediation function remained within a healthy range. The mean NPL ratio of 2.8256% was still below the maximum threshold of 5%, whereas the mean PDN of 1.2294% indicates a relatively low level of foreign exchange risk. In terms of profitability, the mean ROA of 1.8854%, ROE of 9.7430%, and NIM of 5.0806% indicate that the banks had a relatively good ability to generate profits. However, the relatively high standard deviation of ROE, together with its maximum value of 95.44%, indicates the presence of an outlier that needed to be addressed before conducting the factor analysis.

Outlier treatment and data screening

According to Suparwito et al. (2024), an outlier is an observation with a value that differs significantly from most other observations. Outliers may arise from measurement errors, data processing errors, or genuine anomalies. Therefore, outliers need to be properly identified and treated because they may affect the data distribution and lead to misleading analytical conclusions.

Screening of the descriptive statistics and the distribution of BOPO, ROA, and ROE identified the 2021 observation of Bank Raya Indonesia Tbk. (AGRO), with BOPO of 287.86%, ROA of 14.75%, and ROE of 95.44%, as an extreme outlier, reflecting the bank's transition to a digital-bank business model in that year. Removing this single observation significantly improved the suitability of the data, as indicated by the increase in the KMO value from 0.517 (n = 104, "poor") to 0.712 (n = 103, "acceptable"). Therefore, the subsequent factor analysis was conducted using 103 observations (the final model).

Pearson correlation matrix

Table 2. Pearson correlation matrix (n = 103, final model)

	BOPO	CAR	LDR	NPL	PDN	ROA	ROE	NIM
BOPO	1	0.19	−0.07	0.50	0.09	−0.90	−0.77	−0.30
CAR	0.19	1	0.49	0.14	−0.29	−0.10	−0.39	0.22
LDR	−0.07	0.49	1	−0.17	−0.17	0.13	−0.15	0.25
NPL	0.50	0.14	−0.17	1	−0.01	−0.45	−0.35	−0.40
PDN	0.09	−0.29	−0.17	−0.01	1	−0.10	0.13	−0.12
ROA	−0.90	−0.10	0.13	−0.45	−0.10	1	0.75	0.38
ROE	−0.77	−0.39	−0.15	−0.35	0.13	0.75	1	0.10
NIM	−0.30	0.22	0.25	−0.40	−0.12	0.38	0.10	1

The correlation matrix shows strong correlations among several pairs of variables, particularly between BOPO and ROA (−0.90), ROA and ROE (0.75), BOPO and ROE (−0.77), as well as CAR and LDR (0.49). These strong correlation patterns provide initial evidence that these variables can be grouped into the same factor, indicating that the data are suitable for dimensionality reduction through factor analysis.

Assessment of the suitability of factor analysis

Table 3. Sampling adequacy: KMO and Bartlett's Test, and Measure of Sampling Adequacy (MSA) per variable

Panel A. Overall suitability tests (KMO and Bartlett's Test of Sphericity)		
Test	**Model A (n = 104, with outlier)**	**Model B (n = 103, FINAL)**
KMO Measure of Sampling Adequacy	0.517 (Poor)	0.712 (Average)
Bartlett — Approx. Chi-Square	328.310	424.990
Bartlett — df	28	28
Bartlett — Sig.	0.000	0.000
Number of factors (eigenvalue > 1)	3	2
Panel B. Measure of Sampling Adequacy (MSA) per variable, final model (n = 103)		
Variable	**MSA**	**Category**
BOPO	0.736	Average
CAR	0.632	Mediocre
LDR	0.591	Poor
NPL	0.751	Average
PDN	0.572	Poor
ROA	0.699	Mediocre
ROE	0.800	Meritorious
NIM	0.671	Mediocre

In the final model, the KMO value of 0.712 falls into the acceptable ("average") category. Bartlett's Test of Sphericity was statistically significant (Approx. Chi-Square = 424.990; df = 28; Sig. = 0.000 < 0.05), indicating that the correlation matrix is not an identity matrix and that the variables have adequate correlations. Therefore, the data are suitable for factor analysis. Sampling adequacy at the individual variable level, evaluated using the Measure of Sampling Adequacy (MSA) values on the diagonal of the anti-image correlation matrix, is presented in Panel B of Table 3. All variables had MSA values of ≥ 0.50; therefore, no variables needed to be excluded from the analysis. LDR (0.591) and PDN (0.572), however, are only marginally above this threshold and are classified as "Poor" under Kaiser's (1974) guidelines; this borderline adequacy is discussed further as a limitation.

Factor extraction and total variance explained

Table 4. Total variance explained

Component	**Initial Eigenvalue**	**% of Variance**	**Cumulative %**	**Rotation: % of Variance**	**Rotation: Cumulative %**
1	3.151	39.391	39.391	39.390	39.390
2	1.941	24.260	63.651	24.261	63.651
3	0.944	11.794	75.445	—	—
4	0.744	9.297	84.743	—	—
5	0.599	7.488	92.231	—	—
6	0.362	4.528	96.759	—	—
7	0.179	2.239	98.998	—	—
8	0.080	1.002	100.000	—	—

Extraction method: Principal Component Analysis.

Based on Table 4, two components had eigenvalues greater than 1, namely the first component (3.151) and the second component (1.941). Collectively, these two factors explained 63.651% of the total variance in the data.

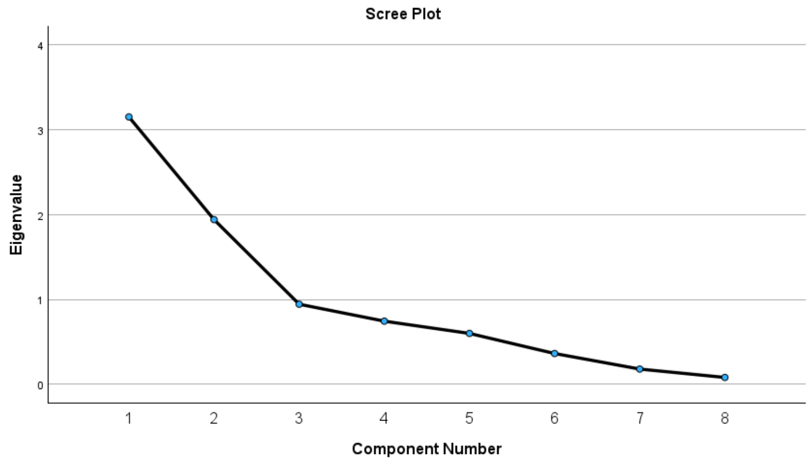

Figure 2. Scree plot of eigenvalues

The scree plot shown in Figure 2 confirms the determination of the number of factors. The eigenvalues decreased sharply from the first component to the second component. After that, the curve began to level off and formed a relatively flat pattern starting from the third component, where the eigenvalue was already below 1. The elbow point occurred after the second component, indicating that retaining two factors was the most appropriate solution.

Communalities

Table 5. Communalities and component/factor loadings before and after varimax rotation

Variable	Communality (Extraction)	Unrotated Component 1	Unrotated Component 2	Rotated Factor 1	Rotated Factor 2	Dominant Factor
BOPO	0.878	−0.937		−0.937		Factor 1
CAR	0.717		0.806		0.808	Factor 2
LDR	0.591		0.765		0.765	Factor 2
NPL	0.462	−0.662		−0.663		Factor 1
PDN	0.271		−0.520		−0.520	Factor 2
ROA	0.872	−0.929		0.930		Factor 1
ROE	0.821	0.837	−0.348	0.834	−0.356	Factor 1
NIM	0.480	0.445	0.530	0.450	0.527	Factor 2

Extraction method: Principal Component Analysis (initial communalities = 1.000 for all variables). Bold-loading criterion: |loading| > 0.50. Rotation method: Varimax.

The communalities results, presented in the Communality column of Table 5, indicate that BOPO had the highest extraction value (0.878), followed by ROA

(0.872) and ROE (0.821), indicating that these three variables were best explained by the extracted factors. In contrast, PDN had, by a wide margin, the lowest communality value (0.271) — well below the next-lowest variable, NPL (0.462) — indicating that PDN is comparatively weakly represented by the two-factor solution. PDN was nonetheless retained because it still loads meaningfully (> 0.50) on the second factor and theoretically represents market risk; this comparatively weak communality is acknowledged as a limitation in Section 5.4, and readers should interpret PDN's contribution to the Capital-Liquidity-Market Risk Factor with some caution.

A reliability statistic such as Cronbach's alpha for the indicators comprising each factor was not computed in this study, consistent with the exploratory, dimension-reduction purpose of the analysis; future studies could report this as a supplementary internal-consistency check.

Factor rotation (rotated component matrix)

The Unrotated Component 1 and Unrotated Component 2 columns of Table 5 present the initial, unrotated component matrix produced by the Principal Component Analysis extraction. At this stage, Component 1 is defined mainly by BOPO (−0.937), ROA (−0.929), ROE (0.837), and NPL (−0.662), while Component 2 is defined mainly by CAR (0.806) and LDR (0.765). However, several variables show cross-loadings on both components, most notably ROE (−0.348 on Component 2) and NIM (0.445 on Component 1 and 0.530 on Component 2), which makes the substantive interpretation of each component ambiguous in its unrotated form. Varimax rotation is therefore applied to redistribute the variance across the two components while preserving their orthogonality, so as to sharpen each variable's association with a single dominant factor and produce a more interpretable structure, as presented in the Rotated Factor 1 and Rotated Factor 2 columns of Table 5.

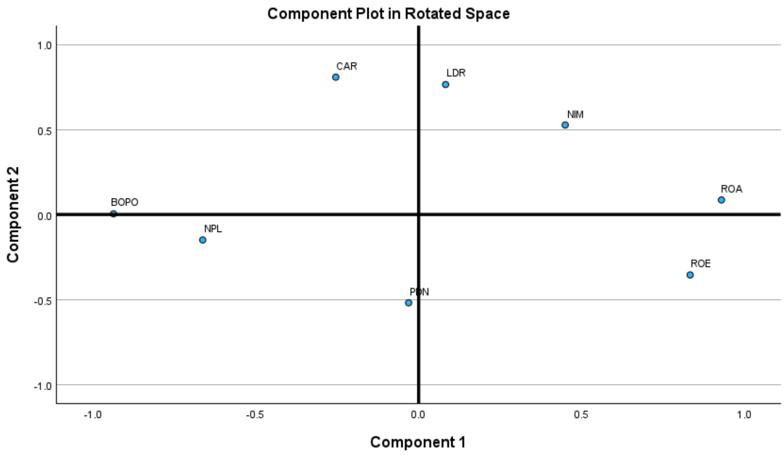

Figure 3. Factor loading plot after varimax rotation

Based on Table 5 and Figure 3, each variable was assigned to the factor on which it had the highest loading value (criterion: > 0.50). Factor 1 consists of BOPO (−0.937), NPL (−0.663), ROA (0.930), and ROE (0.834). Factor 2 consists of CAR (0.808), LDR (0.765), NIM (0.527), and PDN (−0.520). The NIM variable exhibited a slight cross-loading (Factor 1 = 0.450; Factor 2 = 0.527). However, NIM was retained in Factor 2 because it had a higher loading on that factor, indicating that its contribution was more dominant to Factor 2.

Factor naming and interpretation

Table 6. Naming and interpretation of the extracted factors

Factor	Forming Indicators (|loading| > 0.5)	Factor Name (Interpretation)	Highest Loading
Factor 1	BOPO (−0.937), NPL (−0.663), ROA (0.930), ROE (0.834)	Profitability-Efficiency-Credit Quality Factor	BOPO (−0.937)
Factor 2	CAR (0.808), LDR (0.765), NIM (0.527), PDN (−0.520)	Capital-Liquidity-Market Risk Factor	CAR (0.808)

Source: Processed by the authors, 2026

Factor 1 was named the Profitability-Efficiency-Credit Quality Factor because it consists of BOPO, NPL, ROA, and ROE. BOPO and NPL have negative loadings, whereas ROA and ROE have positive loadings. These results indicate that banks with higher profitability tend to exhibit better operational efficiency and better credit quality, whereas lower profitability is associated with greater operational inefficiency and a higher level of non-performing loans. Therefore, Factor 1 represents the primary dimension reflecting bank performance and overall financial soundness.

Factor 2 was named the Capital-Liquidity-Market Risk Factor because it consists of CAR, LDR, NIM, and PDN. CAR, LDR, and NIM have positive loadings, whereas PDN has a negative loading. These results indicate that banks with stronger capital positions tend to have a greater ability to extend loans and generate interest income, while maintaining market risk at a more controlled level. Therefore, Factor 2 represents the dimension of capital, liquidity, and market risk management in banking operations.

Discussion

Adequacy of the intercorrelation among financial ratios

The results of the adequacy tests indicate that the data satisfied the requirements for factor analysis. This is evidenced by the KMO value of 0.712, the statistically significant Bartlett's Test of Sphericity (Sig. = 0.000), and MSA values of ≥ 0.50 for all variables, indicating adequate intercorrelations among the variables. In addition, the removal of one outlier observation (AGRO, 2021) increased the KMO value from 0.517 to 0.712, thereby improving the quality of the data. Under the ERM framework, this reflects the importance of information quality as an input to the risk-identification and risk-assessment process; the data used were consequently able to produce a more representative factor structure for describing banking risk.

Structure of the risk factors identified through factor analysis

The factor analysis resulted in the extraction of two main risk dimensions that explained 63.65% of the total variance, namely the Profitability-Efficiency-Credit Quality Factor and the Capital-Liquidity-Market Risk Factor. These findings indicate that profitability, operational efficiency, and credit quality empirically form the same latent construct, suggesting that these three aspects are interrelated in describing bank performance and financial soundness. Compared with the six-dimension ERM taxonomy set out a priori in Figure 1 (capital, credit, liquidity, operational, profitability, and market risk), the empirical results indicate that these six theoretical dimensions collapse into two broader, empirically distinct latent dimensions in this sample, rather than remaining separable. Furthermore, the second factor indicates that capital, liquidity, and market risk form a distinct risk dimension that complements the first factor. Therefore, these two factors can be used as the two main dimensions for assessing the condition and management of banking risk more comprehensively.

Dominant structural indicator of the profitability-efficiency-credit quality factor

The results indicate that BOPO was the most dominant indicator of the Profitability-Efficiency-Credit Quality Factor, with a factor loading of −0.937. This finding suggests that operational efficiency is strongly associated with bank profitability and credit quality: the lower the BOPO ratio, the better the bank's profitability and credit quality. Consistent with the ERM emphasis on the use of key risk indicators for integrated risk monitoring, BOPO can be used as the primary indicator for monitoring the Profitability-Efficiency-Credit Quality Factor.

Dominant structural indicator of the capital-liquidity-market risk factor

The results indicate that CAR was the most dominant indicator of the Capital-Liquidity-Market Risk Factor, with a factor loading of 0.808. This finding suggests that capital adequacy has a strong relationship with liquidity management, interest income generation, and market risk in the banking sector: banks with stronger capital positions tend to have a greater ability to extend loans, generate interest income, and maintain market risk at a more controlled level. CAR can therefore be used as the primary indicator for monitoring this factor. This interpretation should, however, be tempered somewhat for its market-risk component: as noted in Section 4.7, PDN has the lowest communality (0.271) of the eight indicators and a borderline MSA value (0.572), so the market-risk dimension of this factor is less robustly represented than its capital and liquidity components (CAR and LDR).

Comparison with previous studies

The findings of this study are consistent with those of Widyaningsih and Sampurno (2022), Rosandy and Sha (2022), Ghofirin and Susesti (2023), and

Rosadi and Ramadhan (2024), who found that BOPO has a significant negative effect on ROA. This study extends these findings by demonstrating that BOPO and ROA are very strongly related, resulting in both variables being grouped into the same factor in the factor analysis. In addition, the findings are consistent with Siagian et al. (2024), who reported that CAR and LDR are positively associated with profitability, as reflected by the grouping of these two ratios within the Capital-Liquidity-Market Risk Factor. Unlike previous studies, which employed regression approaches to examine the relationships among variables, this study offers a novel contribution by mapping the latent structure of banking risk through Exploratory Factor Analysis (EFA). The findings demonstrate that various types of banking risk are interrelated and form two main risk dimensions, thereby providing a more comprehensive understanding of banking risk and supporting integrated risk management in accordance with the principles of Enterprise Risk Management (ERM).

Conclusion

Based on the factor analysis of eight financial ratios (CAR, LDR, NPL, BOPO, PDN, ROA, ROE, and NIM) of conventional commercial banks listed on the Indonesia Stock Exchange during 2021–2024, the data proved adequate for Exploratory Factor Analysis (KMO = 0.712; Bartlett's Test significant at Sig. = 0.000; MSA ≥ 0.50 for all variables after removing one outlier observation). Two latent banking-risk factors emerged, jointly explaining 63.65% of total variance: a Profitability-Efficiency-Credit Quality Factor (39.39%; comprising BOPO, NPL, ROA, and ROE, with BOPO as the dominant indicator at a loading of −0.937) and a Capital-Liquidity-Market Risk Factor (24.26%; comprising CAR, LDR, NIM, and PDN, with CAR as the dominant indicator at a loading of 0.808). These results indicate that the eight ratios are interrelated and cohere into two broad risk dimensions, with operational efficiency and capital adequacy standing out as the key indicators for monitoring banking risk.

Theoretically, these findings refine the conventional six-dimension ERM-based risk taxonomy (capital, credit, liquidity, operational, profitability, and market risk) into two empirically distinct latent dimensions, suggesting that several conceptually separate ERM categories move together for Indonesian conventional banks during this period, extending prior regression-based studies that only examined pairwise associations rather than joint latent structure. Practically, BOPO and CAR can serve as parsimonious, high-priority indicators for bank risk officers and regulators (e.g., OJK) in early-warning dashboards representing each factor, alongside continued monitoring of all eight ratios for early signs of divergence. These conclusions should, however, be read in light of several limitations: the two-factor structure is exploratory and has not been cross-validated via Confirmatory Factor Analysis; LDR and PDN showed only borderline MSA values (0.591 and 0.572) and PDN had low communality (0.271), warranting a sensitivity re-run excluding these variables; the outlier-detection method and threshold used to exclude the 2021 AGRO observation require explicit documentation for replicability; the sample is limited to listed conventional banks over a single four-year window, leaving generalizability to Islamic banks, rural banks, other periods, or other ASEAN markets untested; and no international peer-reviewed EFA/PCA-based study on bank financial ratios was identified for direct benchmarking, an area future research should address.

References

Bessis, J. (2015). *Risk management in banking.* 4th edition. Wiley.

Committee of Sponsoring Organizations of the Treadway Commission. (2017). Enterprise risk management: Integrating with strategy and performance. COSO.

Fraser, J. R. S., Quail, R., & Simkins, B. (2021). *Enterprise risk management: Today's leading research and best practices for tomorrow's executives*. 2nd edition. John Wiley & Sons.

Ghofirin, M., & Susesti, D. A. (2023). Analisis pengaruh risiko kredit dan risiko operasional terhadap profitabilitas bank umum BUMN yang terdaftar di BEI periode 2021–2022. *Accounting and Management Journal, 7*(2), 56–62. https://doi.org/10.33086/amj.v7i2.4818

Gina, F. I., Nopiyanti A., Cahyani I. D., Fadila A., Fajrin I. A., Marlina, Arrosyid M. R., Hidayati S., Ramadhani R. B., Wahyudi, Fahrezi Z., & Tristiarto, Y. (2025). *Dinamika kinerja keuangan bank*. Deepublish Digital.

Hartati, L. (2024). *Manajemen keuangan nilai perusahaan dengan mediasi manajemen laba.* Selat Media.

Harun, C. A., Deriantino, E., & Agung, J. (2021). *Kebijakan makro prudensial di Indonesia: Konsep, kerangka, dan implementasi.* Rajawali Pers.

Kasmir. (2021). *Manajemen perbankan.* Rajawali Pers.

Lasiyono, U., & Sulistiyawan, E. (2024). *Metode penelitian kuantitatif.* CV. Mega Press Nusantara.

Rosadi, R. M. V., & Ramadhan, Y. (2024). Contribution of CAR, NPL, LDR, BOPO, and NIM to the return on assets of regional development bank. *Management Studies and Entrepreneurship Journal,* *5*(2), 3802–3818. https://journal.yrpipku.com/index.php/msej/article/view/4305

Rosandy, N., & Sha, T. L. (2022). Pengaruh CAR, NIM, LDR, dan BOPO terhadap ROA pada perbankan di BEI. *Jurnal Multiparadigma Akuntansi,* *4*(4), 1566–1576. https://journal.untar.ac.id/index.php/jpa/article/view/21373

Rose, P. S., & Hudgins, S. C. (2013). *Bank management and financial services.* McGraw-Hill.

Saunders, A., & Cornett, M. M. (2019). *Financial institutions management.* McGraw-Hill.

Silitonga, D. (2022). *Kinerja keuangan dan profitabilitas bank.* Zahira Media Publisher.

Spearman, C. (1904). “General intelligence,” objectively determined and measured. *The American Journal of Psychology,* *15*(2), 201–292. https://doi.org/10.2307/1412107

Suparwito, H., Gunawan, R., Binanto, I., Widyastuti, W., & Kumalasanti, R. A. (2024). *Pengantar manajemen data.* Sanata Dharma University Press.

Syfa, A. N., & Dailibas (2023). Pengaruh CAR dan BOPO terhadap ROA bank umum syariah di Indonesia. *Jurnal Ekonomi Syariah dan Bisnis. 6(1), 49-59.* https://doi.org/10.31949/maro.v6i1.4105

Widyaningsih, N., & Sampurno, R. D. (2022). Analisis pengaruh CAR, NIM, BOPO, NPL dan LDR terhadap kinerja keuangan perbankan selama pandemi Covid-19. *Diponegoro Journal of Management,* *11*(5), 1-15. https://ejournal3.undip.ac.id/index.php/djom/article/view/36586

Yam, J. H. (2023). *Non-performing loan dan bank sustainability performance.* Deepublish.

Yulianto, H. (2024). *Matematika bisnis 1*. Sagusatal Indonesia.