



RESEARCH ARTICLE

A Hybrid MCDM Framework for Assessing Financial Resilience and Trend Dynamics in Indian Commercial Banks

Priya Das^{1,*} and Subir Kumar Sen²

¹Research Scholar, Department of Commerce, Tripura University, Agartala, 799022, India and ²Professor, Department of Commerce, Tripura University, Agartala, 799022, India

*Corresponding author. priya568das@gmail.com

Received on 1 January 2026; Accepted on 20 May 2026

Abstract

Assessing financial resilience in the banking sector requires an integrated framework that captures both cross-sectional strength and long-term resilience dynamics. In this study, financial resilience of Indian commercial banks during the period 2013–2024 is assessed by using a hybrid MCDM and non-parametric trend analysis approach. Eleven financial indicators covering solvency, asset quality, efficiency, and profitability are included in a composite resilience framework, and criterion weights were objectively determined using the MEREC method. The technique RAM is used to calculate annual composite resilience scores and ranks the 29 commercial banks. A Mann–Kendall time-series analysis is also applied to the final RAM scores to analyze long-term monotonic trends in bank-level and sector-wide resilience. The results showed that RAM scores are tightly clustered across banks, suggesting structural convergence in resilience levels. However, Kruskal–Wallis non-parametric test showed statistically significant differences in the banks' relative financial resilience across the study period. The MEREC–RAM ranking result showed Kotak Mahindra Bank Ltd. and Tamilnad Mercantile Bank Ltd. consistently appeared among top at the rankings. While, the Mann–Kendall trend test revealed significant Improvement in the resilience of CSB Bank Ltd. and Bank of Maharashtra over the study period. Overall, combining year-wise relative rankings and monotonic resilience dynamics enables a comprehensive assessment of the stability of the Indian banking sector, which can offer key insights for regulators, policymakers, and bank management in strengthening the long-term financial resilience of the sector.

Key words: Banks, Financial Resilience, MCDM, MEREC, RAM, Mann-Kendall Trend Analysis

JEL codes: G21, G28, G32, C44, D81

1. Introduction

Financial resilience is the ability of an institution to manage, respond to, and bounce back from financial challenges such as economic downturns, reduced earnings, or unforeseen costs. For banks and other financial institutions, the financial resilience refers to the ability to withstand shocks, adapt to changing economic conditions, and maintain stability while continuing to meet obligations and support economic activities[1, 2]. In the context of emerging economies, where financial systems often face volatility, weak governance, and high exposure to non-performing assets (NPAs), evaluating the resilience of banks is particularly crucial[3, 4]. The resilience of financial systems is influenced by several factors, such as firm characteristics, capital adequacy, liquidity management, risk governance, and their ability to respond to external shocks[5]. Assessing financial resilience enables regulators and policymakers to identify

vulnerabilities and design regulatory frameworks that enhance risk management and recovery mechanisms[2].

The Indian banking sector has experienced significant structural changes in the past decades. The heavily regulated regime of the 1980s constrained were limiting operational efficiency of Indian banks and their ability to respond to a rapidly expanding economy[6–8]. However, the economic reforms of the early 1990s, which included deregulation, partial privatisation of public sector banks, and interest rate liberalisation, brought improvements in productivity, competitiveness, and risk management practices[6, 9–11]. Conversely, the post-global financial crisis period highlighted persistent weaknesses in banking systems around the world, including India, in the form of huge NPAs and governance issues[12, 13]. The evolution of the banking sector in India has built upon previous structural reforms and has moved towards a more risk sensitive and resilient regulatory framework. This evolution has

been guided by the adoption of Basel I and II capital adequacy standards, the introduction of risk-based supervision, and governance reforms in public sector banks aimed at enhancing asset quality, transparency, and prudential discipline[14]. These efforts laid the groundwork for more specific post-crisis reforms, such as the Asset Quality Review (AQR) and the Insolvency and Bankruptcy Code (IBC) in 2015–2016 that enhanced balance-sheet recognition and codified mechanisms for stress resolution[15, 16]. Although greater regulation has led to better governance and operational efficiency, there is some evidence that heavier compliance requirements can reduce profitability and internal capital generation, particularly in times of economic stress[17]. In 2018, the Punjab National Bank (PNB) scam revealed serious gaps in internal controls, governance mechanisms, and risk oversight in Indian banks. It demonstrated the need for stronger processes, transparency, and institutional resilience to avoid systemic vulnerabilities [18]. At the same time, the digitalization of banking services has brought new operational risks[19].

These developments point to some of the ongoing challenges faced by the Indian banking sector in sustaining financial resilience throughout cyclical stress, rising NPAs, and balance-sheet pressures. Commercial banks, particularly public sector banks, which account for a substantial share of total banking assets, have remained vulnerable to capital adequacy constraints, asset quality deterioration, and volatility in profitability. Such vulnerabilities underline the importance of continuously monitoring the stability of banks and their capacity to absorb shocks arising from macroeconomic fluctuations and structural adjustments.

Therefore, banking sector resilience should be systematically and multidimensionally assessed to explore how banks cope with financial stress and adapt to regulatory and economic changes. In this context, this study aims to evaluate the financial resilience of Indian commercial banks over 12 years (2013–2024) using a multi-criteria decision-making (MCDM) framework that incorporates the Method based on the Removal Effects of Criteria (MERECE)-based objective weighting and the Root Assessment Method (RAM), supported by non-parametric trend analysis. The Method RAM is relatively new and first applied in measuring banking sector performance. The MERECE-RAM approach can be used to construct composite resilience scores based on deviations from reference performance levels. It allows consistent aggregation of heterogeneous financial indicators without excessive sensitivity to scaling assumptions[20, 21]. This framework can be combined with the Mann–Kendall trend test to compare the relative resilience rankings and their evolution over time, extending MCDM applications beyond static performance comparisons. The unique methodology of the current study is the integration of the impact-driven weighting scheme with a transparent composite scoring approach and a dynamic time-series evaluation that does not rely on the subjective judgments or correlation-based weights used in other studies. Instead this model built on a method that assigns weights by evaluating the contribution of each indicator to the overall system performance[22].

Accordingly, the present study is organized into five major sections. Section 1 presents a brief introduction of the study; Section 2 outlines the background of the study, mentioning the relevant literature, as well as hypotheses development based on relevant theories. Section 3 presents the methodological steps and procedures, Section 4 discusses the major findings using tables and figures, and finally, Section 5 ends with the study

conclusions mentioning managerial and policy implications, and future research directions.

2. Background of the Study

2.1. Financial Resilience Background

Financial resilience has become a key determinant in understanding how individuals, households, institutions, and economies handle and recover from financial shocks. It generally refers to the ability to maintain stability and well-being during disruptions by combining financial resources, skills, and institutional support. This idea encompasses proactive strategies, including accumulating savings, diversifying income sources, and utilizing effective financial tools, as well as having the capacity to recover or even advance to a better financial position[23]. Salignac et al.[1] proposed a foundational framework that explored the concept of financial resilience at the household and community levels in Australia. The study demonstrated the role that resources, skills, and access to opportunities play in resilience. This work was further extended to a global scale by Klapper and Lusardi[24], who showed that financial literacy is a significant predictor of financial resilience at both the individual and household levels, as well as over time[25]. Hamid et al.[4] investigated the determinants of financial resilience in the context of an emerging economy in Malaysia, highlighting the key role that savings, income diversification, and access to credit play in enabling individuals and households to build financial resilience. Salignac et al.[2] extended this to developing economies, where institutional and policy supports for national financial resilience were found to contribute to inclusive economic development. Jansson[26] linked financial resilience to firms, noting that financial position, profitability, and ownership structures impact a firm's ability to withstand downturns. Sreenivasan and Suresh[27] examined start-ups and found that good liquidity management, innovation, and preparedness help new entrepreneurs to manage change. In a study of U.S. households during the COVID-19 pandemic, Clark and Mitchell[28] found that fiscal assistance programs and savings buffers were important for individual financial resilience.

Financial resilience in banking and other financial institutions has been studied extensively, including international banks during the global financial crisis[29], banking systems around the world[30], the U.S. banking system[31], and a loan-level analysis of financial institutions in Mexico[32]. Alam et al. [33] conducted research on corporate resilience among firms in Bangladesh, specifically the relationship between corporate ownership patterns and the resilience of firms, Daadmehr[34] proposed a composite financial resilience index for workplaces and firms, which combines the multi-dimensional matrices (liquidity, leverage, and sustainability practices). Chen and Sun[35] presented an econometric approach to measuring financial resilience across institutions and economies that combine dynamic panel modelling and stress-testing indicators to capture the temporal response of financial entities to shocks.

2.2. MCDM in Bank Performance Evaluation

MCDM techniques have been extensively used for assessing bank performance in different institutional and regional contexts[36]. Most empirical studies have grouped MCDM approaches into criteria weighting methods and outranking methods. Studies have combined the two types of MCDM tools to get a robust performance ranking. AHP–TOPSIS and IV–TOPSIS was used to evaluate listed private banks in India,

which consistently showed the superiority of HDFC Bank[37], and a CRITIC-based TOPSIS framework was incorporated to evaluate public sector banks in India, which showed persistent performance differences[38]. Such hybrid frameworks have been used internationally. Nguyen et al. [39] and Yazdi et al. [40] showed that bank performance rankings during the COVID-19 period are contingent on the weighting and aggregation methods, and that objective weighting schemes are important.

Various alternative weighting and ranking methods have been compared to improve methodological robustness (e.g., Ünlü et al. [41], Ünvan & Ergenç [42], Wanke et al. [43], Sama et al. [44]). Recent contributions have examined hybrid and integrated models that combine subjective and objective factors to increase discrimination power and ranking stability[45–47]. Mohan and Irfan[8] also explained how artificial intelligence with MCDM tools was used to assess the performance of banks in India.

The literature confirms the effectiveness of MCDM frameworks in assessing bank performance; however, most studies remain confined to static, cross-sectional performance rankings. Limited attention has been paid to integrating MCDM-based composite indices with dynamic analyses that capture performance evolution over time, particularly in the context of financial resilience. This gap motivates the present study’s use of an objective weighting scheme and a composite assessment framework that can support both ranking and temporal trend analysis.

2.3. Hypotheses Development

Financial resilience can be conceptualized as a multi-dimensional construct reflecting a bank’s ability to absorb shocks, adapt to adverse conditions, and maintain core functions over time[48, 49]. While the theory of resilience posits that a bank’s solvency strength, asset quality, operational efficiency, and profitability will result in resilience. However, the theory does not suggest that resilience will improve in a linear or monotonic way, especially in banking systems subject to regulatory reform, economic cycles, and changing risk profiles.

From a regulatory perspective, the Capital Buffer Theory[50, 51], as formalized by the Basel framework, states that capital adequacy and provisioning requirements are first and foremost intended to maintain minimum stability thresholds rather than to continually improve performance. Stricter asset classification standards, supervisory reviews, and corrective action frameworks are some of the regulatory interventions that force banks to rebalance their capital structures and portfolios[52]. These measures may increase system-wide stability, but it is uncertain how they will ultimately affect composite resilience measures because improvements in capital or asset quality may put short-term pressure on profitability and efficiency.

Moreover, Dynamic Capability Theory[53, 54] provides a strategic view, which states that resilience can only be improved over the long term if a bank has the ability to perceive upcoming threats and reorganize its resources in the face of evolving circumstances[54]. Due to differences in ownership structures, managerial skills, and strategic adaptability, not all banks tend to react to environmental change or regulatory compliance with higher overall resilience. Consequently, banks may exhibit heterogeneous and non-uniform resilience trajectories over time. Combined, these theoretical perspectives suggest that, at the aggregate level, bank financial resilience may not follow a systematic or statistically discernible long-term trend.

Accordingly, the following null hypothesis is formulated:

H_0^1 : There is no statistically significant monotonic trend in the composite RAM-based financial resilience scores of Indian commercial banks over the study period.

H_0^2 : There is no statistically significant difference between private and public sector banks in India over the study period.

3. Methodology

This study examines the financial resilience of selected commercial banks in India from 2013-2014 to 2024-2025. The study employs an integrated MEREC-based RAM approach within an MCDM framework to determine the weights of criteria, rank banks based on their financial resilience composite scores, and then applies the Mann-Kendall trend analysis to identify the performance dynamics and resilience trends of banks over the years. It also employed Welch two-sample t-test and Kruskal–Wallis non-parametric test to examine bank specific and year-wise significant differences in resilience scores. The study used equal weights and entropy-based weighting to check for the sensitivity of weight change on the ranking outcomes. It further employed TOPSIS, RATMI, and MARCOS techniques to examine the robustness of the proposed MEREC-RAM model. Finally, the Kendall’s tau coefficients are determined to analyse the concordance of ranking outcomes across the methods. Figure 1 presents the conceptual framework designed for conducting the research.

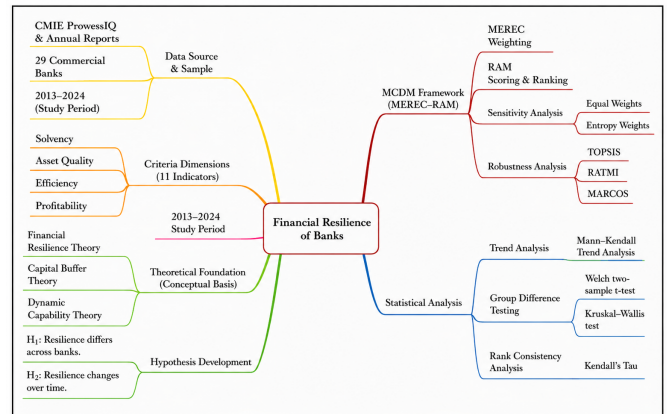


Figure 1. Conceptual Framework of the Study. (Source: Authors’ Compilation)

Accordingly, the study integrated secondary data from the CMIE database and banks’ annual reports from 2013 to 2024. The data collected for a sample of 29 commercial banks out of which 17 are private and 12 public sector counterparts. The study performed robust data cleaning, accounting for any missing data. Companies with continuous missing data for multiple variables were excluded from the analysis. To enhance the accuracy of the data, no approximation or rounding has been performed. Table 1 outlines the study sample, including bank codes.

Financial resilience in banks refers to the ability to absorb shocks, maintain core financial functions, and adapt to adverse economic and regulatory conditions. In line with the banking resilience and financial stability literature, resilience is conceptualised as a multidimensional construct encompassing solvency

| Code | Name of Bank | Ownership | Code | Name of Bank | Ownership |
|------|-----------------------|-----------|------|-------------------------------|-----------|
| CB1 | Axis Bank Ltd. | Private | CB16 | Indusind Bank Ltd. | Private |
| CB2 | Bank of Baroda | Public | CB17 | Jammu & Kashmir Bank Ltd. | Private |
| CB3 | Bank of India | Public | CB18 | Karnataka Bank Ltd. | Private |
| CB4 | Bank of Maharashtra | Public | CB19 | Karur Vysya Bank Ltd. | Private |
| CB5 | CSB Bank Ltd. | Private | CB20 | Kotak Mahindra Bank Ltd. | Private |
| CB6 | Canara Bank | Public | CB21 | Punjab & Sind Bank | Public |
| CB7 | Central Bank of India | Public | CB22 | Punjab National Bank | Public |
| CB8 | City Union Bank Ltd. | Private | CB23 | RBL Bank Ltd. | Private |
| CB9 | DCB Bank Ltd. | Private | CB24 | South Indian Bank Ltd. | Private |
| CB10 | Dhanlaxmi Bank Ltd. | Private | CB25 | State Bank of India | Public |
| CB11 | Federal Bank Ltd. | Private | CB26 | Tamilnad Mercantile Bank Ltd. | Private |
| CB12 | HDFC Bank Ltd. | Private | CB27 | UCO Bank | Public |
| CB13 | ICICI Bank Ltd. | Private | CB28 | Union Bank of India | Public |
| CB14 | Indian Bank | Public | CB29 | Yes Bank Ltd. | Private |
| CB15 | Indian Overseas Bank | Public | | | |

Table 1. Selected Commercial Banks (CB). (Source: Authors' Compilation)

| Resilience | Code | Attributes | Descriptions | Expected Outcome |
|----------------|------|------------|---|------------------|
| Solvency | C1 | CAR | $\frac{\text{Tier I Capital} + \text{Tier II Capital}}{\text{Risk} - \text{Weighted Assets}}$ | Max |
| | C2 | Tier-1 CAP | $\frac{\text{Tier I Capital}}{\text{Risk} - \text{Weighted Assets}}$ | Max |
| | C3 | D/E | $\frac{\text{Total debt}}{\text{Shareholders' Equity}}$ | Min |
| Assets Quality | C4 | GNPA | $\frac{\text{Gross NPAs}}{\text{Gross Advances}}$ | Min |
| | C5 | NNPA | $\frac{\text{Net NPAs}}{\text{Net Advances}}$ | Min |
| | C6 | LGR | $\frac{\text{Total Advances}_t - \text{Total Advances}_{t-1}}{\text{Total Advances}_{t-1}}$ | Min |
| | C7 | PCR | $\frac{\text{Total Provisions}}{\text{Gross NPAs}}$ | Max |
| Efficiency | C8 | C-I | $\frac{\text{Operating Expenses}}{\text{Total Income}}$ | Min |
| | C9 | C-D | $\frac{\text{Total Advances}}{\text{Total Deposits}}$ | Min |
| Profitability | C10 | ROA | $\frac{\text{Net Profit}}{\text{Total Assets}}$ | Max |
| | C11 | ROE | $\frac{\text{Net Profit}}{\text{Shareholders' Equity}}$ | Max |

Table 2. Description of Selected Variables (Criteria). (Source: Authors' Compilation)

strength, asset quality, operational efficiency, and profitability. Therefore, the criteria or resilience indicators are grouped into four major dimensions: Solvency, Asset Quality, Efficiency, and Profitability, and treated as indicators of banks' financial resilience. Eleven financial ratios are incorporated under the four dimensions of the resilience framework. Table 2 presents the descriptions of the resilience indicators (variables). The variables are selected and established based on the available literature and related concepts and theories on banks' performance and financial resilience[3, 4, 37, 38, 43, 55–63].

3.1. MEREC Approach

Keshavarz et al.[22] proposed a new objective weighting method, MEREC, which utilizes the removal effect on alternatives to determine attribute weights. In contrast to previous criteria weight calculation techniques, the MEREC method

relies on how the removal of conditions affects the total effects of substitutes[64, 65]. Higher weights are assigned to attributes with greater performance effects, and smaller weights are given to attributes with smaller performance effects. It gives an innovative approach to the criteria weight calculation technique.

The method follows the following six steps[22, 64, 65]:

Step 1: Construct the decision/evaluation matrix. The multi-criteria decision-making incorporates an $m \times n$ matrix where m is the number of alternatives and n is the number of criteria

$$X = x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

The elements of the matrix are denoted by x_{ij} , where $i = 1, \dots, m$, and $j = 1, \dots, n$. The values in the matrix should be greater than zero ($x_{ij} > 0$) as well as a positive integer. Subsequently, any negative criteria values will be adjusted using the proper method.

Step 2: Normalize the decision matrix n_{ij}

Simple linear normalization procedure is applied to scale the elements of the decision matrix.

$$n_{ij} = \frac{x_{ij}}{\max x_j} \text{ if } j \in B \quad (2)$$

$$n_{ij} = \frac{\min x_j}{x_{ij}} \text{ if } j \in C \quad (3)$$

Where B is the benefit group of criteria (Max-type), and C represents the cost criteria (Min-type)

Step 3: Calculate the overall performance P_i

In this step, a logarithmic aggregation measure with equal weights for all criteria is employed to compute the overall performance values P_i . This measure is based on a non-linear function. Based on the normalized decision matrix obtained in the previous step, larger values of n_{ij} indicate better performance of the alternatives.

$$P_i = \ln \left(1 + \left(\frac{1}{n} \sum_{j=1}^n |\ln(n_{ij})| \right) \right) \quad (4)$$

Step 4: Determine the performance of alternatives by removing each criterion

This step evaluates the effect of each criterion on the overall performance of the alternatives by excluding one criterion at a time. Let P'_{ij} denote the overall performance of the i^{th} alternative when the j^{th} criterion is removed.

The performance value after removing the j^{th} criterion is computed as:

$$P'_{ij} = \ln \left(1 + \left(\frac{1}{n-1} \sum_{k=1, k \neq j}^n |\ln(n_{ik})| \right) \right) \quad (5)$$

Step 5: The summation of absolute deviations

In this step, we calculate the removal effect of the j^{th} criterion based on the values obtained in steps 3 and 4. Let R_j is the removal effect of the j^{th} criterion

$$R_j = \sum_{i=1}^m |P'_{ij} - P_i| \quad (6)$$

Step 6: Determine the final weights of the criterion

$$W_j = \frac{R_j}{\sum_{j=1}^n R_j} \quad (7)$$

3.2. RAM Method

The Root Assessment Method (RAM) aims to derive the utility value of each alternative by aggregating its scores over decision criteria. The Method was first applied to sustainability-focused multi-criteria decision problems, addressing complex evaluations with transparent ranking logic[20]. Subsequent studies extended its application to energy technology selection, manufacturing systems, urban and cost-of-living assessment, and comparative methodological analysis, including fuzzy, spherical fuzzy, and neutrosophic environments to manage uncertainty[21, 66–68]. The RAM method is selected in

this bank resilience study, considering its low computational complexity, stable rankings[20], and effective integration with MEREC-based objective weighting, which may outperform conventional outranking MCDM techniques in complex financial evaluations.

The method involves the following major steps[20, 21, 68]:

Step 1: The first step involves forming an initial matrix X. This is preceded by defining the m set of alternatives A_i and a set of n criteria C_i

$$D = x_{ij} = \begin{matrix} A_1 & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ A_m & \begin{bmatrix} x_{m1} & x_{m2} & \cdots & x_{m \times n} \end{bmatrix} \end{matrix} \end{matrix} \quad (8)$$

Where alternatives $i = 1, 2, \dots, m$ and criterion $j = 1, 2, \dots, n$ can be expressed based on the nature of the criteria, i.e., cost (C) or benefit (B).

Step 2: Normalization of the initial matrix (x) using the linear sum normalization

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (9)$$

Where elements x_{ij} represents the elements of the matrix x.

Step 3: Determination of the weighted normalized matrix V

$$V_{ij} = n_{ij} \times w_j \quad (10)$$

Where n_{ij} represents the normalized values calculated in step 2, and w_j represents the MEREC weights.

Step 4: Calculate the aggregates of weighted normalized values of beneficial and non-beneficial criteria for each alternative using the following equations

$$K_{+i} = \sum_{j=1}^n v_{+ij} \quad (11)$$

$$K_{-i} = \sum_{j=1}^n v_{-ij} \quad (12)$$

Whereas K_{+i} is the sum of weighted normalized values of the beneficial criteria and K_{-i} is the sum of weighted normalized values of the cost criteria.

Step 5: Determination of the aggregate relative resilience scores of alternatives using the following function Q_i

$$Q_i = \frac{2 + K_{-i}}{\sqrt{2 + K_{+i}}} \quad (13)$$

The ranking of alternatives relies on the final values Q_i in descending order.

3.3. Mann–Kendall Trend Analysis

To determine whether the financial resilience of individual banks exhibited a monotonic trend over the study period, the univariate Mann–Kendall non-parametric trend test was applied to the composite RAM-based financial resilience scores for each bank from 2013 to 2024. The Mann–Kendall test is widely used for trend detection in time-series data because it does not require assumptions of normality and is robust to outliers.

The test statistic is computed as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (14)$$

Where n is the number of years, x_i , and x_j denote the composite RAM scores observed at time points i and j , respectively, and the sign function $\text{sgn}(\cdot)$ is defined as:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j - x_i > 0, \\ 0, & \text{if } x_j - x_i = 0, \\ -1, & \text{if } x_j - x_i < 0. \end{cases}$$

For sample sizes greater than ten, the statistic S is standardized to a normal variate Z ,

$$\text{Where, } Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases}$$

Here,

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18}$$

It tests the following hypotheses:

- H_0 : No monotonic trend exists in the series
- H_1 : A monotonic trend exists in the series

A positive and statistically significant Z -value indicates an increasing trend in financial resilience, whereas a negative and statistically significant Z -value indicates a decreasing trend. Statistical significance is evaluated at the 5% level ($p < 0.05$).

4. Results and Discussions

4.1. Analysis using MEREK

The study applies a multi-stage MCDM-integrated Mann-Kendall model. Initially, a 29×11 ($m \times n$) decision matrix is developed based on 11 criteria related to 29 banks (alternatives), for each year from 2013-2014 to 2024-2025, using Eq. (1). The relative importance of each criterion or financial resilience indicator is determined using the MEREK weighting method. Then, the weights obtained are integrated into the RAM approach to generate the resilience index. The ranking of banks is determined based on the aggregate function calculated at the end of the RAM approach.

The values in the decision matrix (Eq. (1)) were normalized for each period using Eq. (2) using the linear min-max normalization method to convert all the cost-benefit criteria into the same measurement scale. Subsequently, a logarithmic aggregation measure based on equal criterion weights is applied to the normalized values n_{ij} to compute the P_i values in Eq. (4). The p_i values represent the initial overall performance scores of the alternatives, taking into account all criteria. Accordingly, the modified performance values P'_{ij} are calculated using Eq. (5) by removing one criterion at a time from the set of criteria associated with alternatives, i.e., column-wise elimination. Equation (6) is then used to evaluate the criterion removal effect R_j by measuring the absolute deviation between P'_{ij} and P_i for each alternative i and criterion j . Finally, the criterion weights W_j for each study period are determined using Eq. (7) and are presented in Table 3.

The MEREK results, as shown in Table 3, reveals moderate variation in criteria weights over time. CAR (C1) increases from 0.046 (2013) to 0.123 (2022), reflecting rising regulatory emphasis. Loan growth (C6) fluctuates between 0.064 and 0.092, indicating cyclical sensitivity. Cost efficiency (C8) also varies (0.069–0.098), while ROA (C10) and ROE (C11) remain relatively stable (0.088–0.102). This suggests limited differentiation and a consistently lower role in resilience assessment.

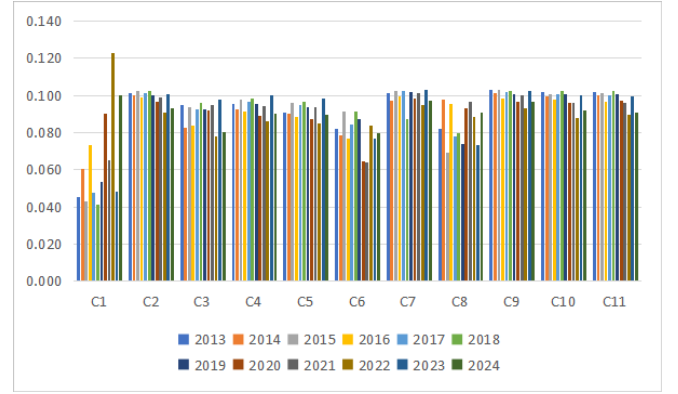


Figure 2. Relative Importance of Financial Resilience Indicators (2013-2024). (Source: Estimated by the authors)

Fig 2 highlights temporal shifts in criteria importance as well as fluctuations in loan growth and efficiency indicators. This reflects impact of real-world events such as the AQR and IBC phases. On the other hand relative weight stability in profitability indicators suggests consistent regulatory and operational frameworks.

4.2. Analysis using RAM

The method RAM evaluated banking resilience by aggregating multiple financial indicators in a structured manner. The first step is to build the initial decision matrix D (Eq. (8)), which summarizes the performance of each banking alternative over all selected resilience indicators. Next it applies linear sum normalization (Eq. (9)) to enable logical comparison across indicators measured in different units. The normalized matrix is then weighted (Eq. (10)) with the MEREK-derived weight coefficients shown in Table 3 to produce the weighted normalized matrix V , which ensures that criteria with higher systemic relevance have a stronger effect on the evaluation.

RAM explicitly accounts for the asymmetric roles of beneficial and non-beneficial criteria by aggregating them separately, as expressed in Equations(11) and (12). K_{+i} is the sum of weighted normalized values of the beneficial criteria and K_{-i} is the sum of weighted normalized values of the cost criteria which are presented in Table 4. Beneficial criteria contribute positively to resilience, whereas non-beneficial criteria capture vulnerability channels. This separation enables the final RAM utility score Q_i , computed using Eq. (13), to reflect the balance between shock-absorption capacity and risk exposure.

Table 5 shows the RAM-based aggregate relative resilience scores (Q_i) of each bank from 2013 to 2024. The (Q_i) scores show a high level of consistency. The values generally fall between about 1.41 and 1.42.

The Q_i values are normalized and presented in Table 6 which shows the financial resilience ranges between 0.995 and

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 2013 | 0.046 | 0.101 | 0.095 | 0.095 | 0.091 | 0.082 | 0.101 | 0.082 | 0.103 | 0.102 | 0.102 |
| 2014 | 0.060 | 0.100 | 0.083 | 0.093 | 0.090 | 0.079 | 0.097 | 0.098 | 0.101 | 0.100 | 0.100 |
| 2015 | 0.043 | 0.103 | 0.094 | 0.098 | 0.096 | 0.091 | 0.103 | 0.069 | 0.103 | 0.100 | 0.101 |
| 2016 | 0.073 | 0.099 | 0.084 | 0.091 | 0.089 | 0.077 | 0.099 | 0.096 | 0.098 | 0.097 | 0.097 |
| 2017 | 0.047 | 0.101 | 0.093 | 0.097 | 0.095 | 0.084 | 0.102 | 0.078 | 0.102 | 0.100 | 0.100 |
| 2018 | 0.041 | 0.103 | 0.096 | 0.098 | 0.097 | 0.092 | 0.087 | 0.080 | 0.102 | 0.102 | 0.102 |
| 2019 | 0.054 | 0.100 | 0.093 | 0.096 | 0.094 | 0.087 | 0.102 | 0.074 | 0.101 | 0.101 | 0.101 |
| 2020 | 0.090 | 0.096 | 0.092 | 0.089 | 0.087 | 0.064 | 0.098 | 0.093 | 0.097 | 0.096 | 0.097 |
| 2021 | 0.065 | 0.099 | 0.095 | 0.094 | 0.093 | 0.064 | 0.101 | 0.097 | 0.100 | 0.096 | 0.096 |
| 2022 | 0.123 | 0.091 | 0.078 | 0.086 | 0.085 | 0.084 | 0.095 | 0.088 | 0.093 | 0.088 | 0.090 |
| 2023 | 0.048 | 0.101 | 0.098 | 0.100 | 0.098 | 0.077 | 0.103 | 0.073 | 0.103 | 0.100 | 0.099 |
| 2024 | 0.100 | 0.093 | 0.080 | 0.090 | 0.090 | 0.080 | 0.097 | 0.091 | 0.096 | 0.092 | 0.091 |

Table 3. Year-Wise Obtained Criteria Weights using the MEREC Approach. (Source: Estimated by the authors)

| | 2013 | | 2014 | | 2015 | | 2016 | | 2017 | | 2018 | | 2019 | | 2020 | | 2021 | | 2022 | | 2023 | | 2024 | | |
|------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-------|
| | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | K_{+i} | K_{-i} | |
| CB1 | 0.019 | 0.015 | 0.019 | 0.015 | 0.021 | 0.018 | 0.018 | 0.018 | 0.017 | 0.022 | 0.014 | 0.020 | 0.017 | 0.019 | 0.018 | 0.016 | 0.019 | 0.017 | 0.014 | 0.014 | 0.018 | 0.018 | 0.018 | 0.018 | 0.013 |
| CB2 | 0.015 | 0.018 | 0.015 | 0.014 | 0.011 | 0.019 | 0.015 | 0.018 | 0.015 | 0.021 | 0.013 | 0.019 | 0.015 | 0.024 | 0.015 | 0.018 | 0.014 | 0.020 | 0.017 | 0.014 | 0.015 | 0.019 | 0.016 | 0.018 | 0.018 |
| CB3 | 0.013 | 0.023 | 0.013 | 0.020 | 0.009 | 0.026 | 0.013 | 0.025 | 0.012 | 0.024 | 0.012 | 0.023 | 0.015 | 0.023 | 0.016 | 0.018 | 0.013 | 0.020 | 0.014 | 0.019 | 0.013 | 0.025 | 0.014 | 0.023 | 0.023 |
| CB4 | 0.016 | 0.021 | 0.019 | 0.023 | 0.012 | 0.023 | 0.009 | 0.027 | 0.013 | 0.021 | 0.005 | 0.025 | 0.016 | 0.019 | 0.016 | 0.014 | 0.015 | 0.014 | 0.019 | 0.010 | 0.020 | 0.013 | 0.021 | 0.015 | 0.015 |
| CB5 | 0.012 | 0.020 | 0.010 | 0.063 | 0.008 | 0.010 | 0.015 | 0.018 | 0.013 | 0.012 | 0.012 | 0.011 | 0.020 | 0.015 | 0.020 | 0.015 | 0.027 | 0.014 | 0.026 | 0.008 | 0.021 | 0.015 | 0.019 | 0.022 | 0.022 |
| CB6 | 0.014 | 0.020 | 0.014 | 0.017 | 0.011 | 0.021 | 0.015 | 0.022 | 0.013 | 0.022 | 0.011 | 0.021 | 0.015 | 0.020 | 0.015 | 0.023 | 0.014 | 0.020 | 0.017 | 0.018 | 0.016 | 0.022 | 0.017 | 0.020 | 0.020 |
| CB7 | 0.010 | 0.027 | 0.013 | 0.022 | 0.009 | 0.023 | 0.010 | 0.024 | 0.008 | 0.024 | 0.007 | 0.022 | 0.014 | 0.025 | 0.015 | 0.020 | 0.012 | 0.024 | 0.012 | 0.017 | 0.013 | 0.021 | 0.015 | 0.018 | 0.018 |
| CB8 | 0.018 | 0.012 | 0.019 | 0.011 | 0.021 | 0.013 | 0.021 | 0.012 | 0.021 | 0.013 | 0.016 | 0.014 | 0.017 | 0.014 | 0.019 | 0.013 | 0.020 | 0.019 | 0.020 | 0.017 | 0.018 | 0.024 | 0.019 | 0.020 | 0.020 |
| CB9 | 0.018 | 0.016 | 0.019 | 0.015 | 0.021 | 0.014 | 0.019 | 0.014 | 0.020 | 0.015 | 0.016 | 0.014 | 0.018 | 0.015 | 0.018 | 0.017 | 0.016 | 0.019 | 0.016 | 0.015 | 0.014 | 0.023 | 0.014 | 0.027 | 0.027 |
| CB10 | 0.006 | 0.022 | 0.008 | 0.032 | 0.011 | 0.011 | 0.016 | 0.026 | 0.016 | 0.013 | 0.013 | 0.016 | 0.017 | 0.014 | 0.015 | 0.030 | 0.009 | 0.021 | 0.011 | 0.022 | 0.008 | 0.017 | 0.009 | 0.021 | 0.021 |
| CB11 | 0.019 | 0.012 | 0.019 | 0.012 | 0.018 | 0.014 | 0.018 | 0.014 | 0.019 | 0.016 | 0.015 | 0.015 | 0.017 | 0.014 | 0.017 | 0.012 | 0.017 | 0.015 | 0.017 | 0.012 | 0.016 | 0.017 | 0.016 | 0.015 | 0.015 |
| CB12 | 0.019 | 0.014 | 0.020 | 0.011 | 0.022 | 0.015 | 0.021 | 0.012 | 0.021 | 0.014 | 0.017 | 0.015 | 0.021 | 0.014 | 0.020 | 0.011 | 0.023 | 0.012 | 0.021 | 0.009 | 0.018 | 0.020 | 0.018 | 0.014 | 0.014 |
| CB13 | 0.019 | 0.020 | 0.019 | 0.020 | 0.020 | 0.022 | 0.019 | 0.020 | 0.019 | 0.021 | 0.015 | 0.019 | 0.017 | 0.016 | 0.019 | 0.012 | 0.023 | 0.013 | 0.022 | 0.010 | 0.020 | 0.016 | 0.020 | 0.013 | 0.013 |
| CB14 | 0.015 | 0.018 | 0.015 | 0.014 | 0.015 | 0.016 | 0.017 | 0.016 | 0.017 | 0.019 | 0.013 | 0.018 | 0.016 | 0.018 | 0.017 | 0.025 | 0.014 | 0.017 | 0.015 | 0.013 | 0.014 | 0.017 | 0.017 | 0.015 | 0.015 |
| CB15 | 0.012 | 0.024 | 0.011 | 0.024 | 0.008 | 0.034 | 0.009 | 0.032 | 0.007 | 0.028 | 0.011 | 0.030 | 0.010 | 0.020 | 0.017 | 0.016 | 0.015 | 0.018 | 0.014 | 0.019 | 0.014 | 0.020 | 0.016 | 0.018 | 0.018 |
| CB16 | 0.019 | 0.016 | 0.018 | 0.016 | 0.022 | 0.017 | 0.021 | 0.014 | 0.021 | 0.017 | 0.015 | 0.020 | 0.017 | 0.017 | 0.018 | 0.013 | 0.019 | 0.014 | 0.020 | 0.011 | 0.018 | 0.017 | 0.011 | 0.017 | 0.017 |
| CB17 | 0.019 | 0.012 | 0.015 | 0.014 | 0.017 | 0.018 | 0.009 | 0.017 | 0.016 | 0.016 | 0.013 | 0.019 | 0.013 | 0.017 | 0.015 | 0.016 | 0.013 | 0.022 | 0.016 | 0.016 | 0.015 | 0.017 | 0.017 | 0.017 | 0.017 |
| CB18 | 0.015 | 0.017 | 0.016 | 0.014 | 0.017 | 0.013 | 0.018 | 0.014 | 0.017 | 0.015 | 0.014 | 0.016 | 0.016 | 0.016 | 0.016 | 0.012 | 0.014 | 0.016 | 0.018 | 0.013 | 0.018 | 0.021 | 0.016 | 0.019 | 0.019 |
| CB19 | 0.017 | 0.014 | 0.018 | 0.011 | 0.020 | 0.012 | 0.018 | 0.012 | 0.018 | 0.015 | 0.015 | 0.018 | 0.017 | 0.016 | 0.018 | 0.016 | 0.017 | 0.016 | 0.019 | 0.009 | 0.018 | 0.013 | 0.019 | 0.016 | 0.016 |
| CB20 | 0.020 | 0.015 | 0.020 | 0.015 | 0.021 | 0.022 | 0.021 | 0.013 | 0.022 | 0.014 | 0.018 | 0.015 | 0.020 | 0.013 | 0.021 | 0.010 | 0.024 | 0.012 | 0.024 | 0.008 | 0.021 | 0.013 | 0.022 | 0.012 | 0.012 |
| CB21 | 0.012 | 0.022 | 0.013 | 0.020 | 0.015 | 0.018 | 0.014 | 0.020 | 0.013 | 0.020 | 0.076 | 0.022 | 0.012 | 0.025 | 0.010 | 0.029 | 0.014 | 0.022 | 0.015 | 0.022 | 0.011 | 0.023 | 0.014 | 0.025 | 0.025 |
| CB22 | 0.014 | 0.023 | 0.014 | 0.021 | 0.010 | 0.028 | 0.014 | 0.021 | 0.008 | 0.026 | 0.008 | 0.023 | 0.016 | 0.022 | 0.015 | 0.024 | 0.010 | 0.024 | 0.011 | 0.021 | 0.012 | 0.020 | 0.018 | 0.019 | 0.019 |
| CB23 | 0.016 | 0.032 | 0.017 | 0.022 | 0.018 | 0.024 | 0.018 | 0.018 | 0.019 | 0.017 | 0.015 | 0.019 | 0.017 | 0.018 | 0.017 | 0.014 | 0.010 | 0.016 | 0.014 | 0.015 | 0.013 | 0.020 | 0.012 | 0.015 | 0.015 |
| CB24 | 0.016 | 0.014 | 0.014 | 0.011 | 0.015 | 0.016 | 0.016 | 0.013 | 0.016 | 0.015 | 0.013 | 0.018 | 0.014 | 0.019 | 0.014 | 0.018 | 0.009 | 0.026 | 0.013 | 0.025 | 0.015 | 0.022 | 0.016 | 0.022 | 0.022 |
| CB25 | 0.015 | 0.023 | 0.015 | 0.017 | 0.016 | 0.023 | 0.016 | 0.020 | 0.015 | 0.023 | 0.012 | 0.021 | 0.016 | 0.018 | 0.016 | 0.018 | 0.015 | 0.019 | 0.016 | 0.015 | 0.015 | 0.021 | 0.015 | 0.017 | 0.017 |
| CB26 | 0.017 | 0.015 | 0.018 | 0.010 | 0.020 | 0.012 | 0.019 | 0.013 | 0.019 | 0.011 | 0.016 | 0.015 | 0.019 | 0.012 | 0.020 | 0.014 | 0.024 | 0.014 | 0.025 | 0.008 | 0.022 | 0.015 | 0.024 | 0.021 | 0.021 |
| CB27 | 0.015 | 0.024 | 0.014 | 0.019 | 0.008 | 0.028 | 0.011 | 0.024 | 0.009 | 0.028 | 0.008 | 0.026 | 0.013 | 0.022 | 0.015 | 0.018 | 0.010 | 0.017 | 0.012 | 0.092 | 0.012 | 0.021 | 0.012 | 0.022 | 0.022 |
| CB28 | 0.014 | 0.022 | 0.014 | 0.021 | 0.014 | 0.022 | 0.014 | 0.025 | 0.011 | 0.024 | 0.010 | 0.025 | 0.014 | 0.025 | 0.015 | 0.029 | 0.014 | 0.023 | 0.015 | 0.018 | 0.016 | 0.019 | 0.018 | 0.016 | 0.016 |
| CB29 | 0.019 | 0.017 | 0.021 | 0.021 | 0.019 | 0.020 | 0.012 | 0.019 | 0.025 | 0.013 | 0.026 | 0.006 | 0.035 | 0.012 | 0.030 | 0.012 | 0.039 | 0.010 | 0.026 | 0.008 | 0.019 | 0.011 | 0.019 | 0.019 | 0.019 |

Table 4. Aggregates of Weighted Normalized Values of the Beneficial (K_{+i}) and Cost (K_{-i}) Criteria

1. This normalization simplified it to compare the scores across banks and over the years. Most banks keep consistently high normalized scores, reflecting strong and stable performance throughout the study period. The limited spread in normalized Q_i values highlights the stability of the banking system, while the observed differences give valuable insights into how banks perform relative to each other. This supports the reliability of the RAM-based evaluation and suggests that the banking system exhibits consistent resilience with limited dispersion in performance levels.

The banks such as CB8, CB11, CB12, and CB20 consistently reflected higher Q_i scores across multiple years. These banks demonstrate minimal fluctuations, reflecting strong adaptability and sustained resilience under uncertainties. In contrast, banks such as CB5, CB6, CB10, and CB15 demonstrates slightly lower Q_i values and maximum variation over time. Although their scores remain within a high range, the observed fluctuations suggest relatively lower stability and sensitivity to macro-level changes compared to the top-performing banks.

Accordingly, Table 7 presents the year-wise ranking results obtained using the MEREC-RAM approach.

The annual RAM-based rankings provide additional insight about banks' relative financial resilience over time. While the

changes in normalized Q_i values between banks are almost negligible, the modest variations discovered have a substantial impact on year-over-year rankings. The narrow dispersion of RAM scores reflects the standardized and highly regulated nature of the Indian banking system under RBI and Basel norms. This demonstrates that even slight changes in performance can affect how banks compare in a competitive market.

A set of banks frequently holds the top ranks. In For instance, Kotak Mahindra Bank Ltd. (CB20) performed exceptionally well, frequently ranking among the top places and achieving first position multiple times, particularly in recent years. Similarly, Tamilnad Mercantile Bank Ltd. (CB26), HDFC Bank Ltd. (CB12) and ICICI Bank Ltd. (CB13) maintained stable ranks throughout the study period. City Union Bank Ltd. (CB8) and Federal Bank Ltd. (CB11) also exhibited relatively high and stable rankings, with minor fluctuations. These banks can be considered as consistently resilient performers within the sample. On the other hand, CSB Bank Ltd. (CB5) reflected significant improvement in rankings from bottom to top ten over the years. Bank of Maharashtra (CB4) also demonstrated significant improvement in rankings by reaching to the second place during 2024.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| CB1 | 1.417 | 1.417 | 1.417 | 1.416 | 1.415 | 1.414 | 1.416 | 1.417 | 1.417 | 1.416 | 1.416 | 1.417 |
| CB2 | 1.415 | 1.416 | 1.414 | 1.415 | 1.414 | 1.414 | 1.414 | 1.415 | 1.414 | 1.416 | 1.415 | 1.415 |
| CB3 | 1.413 | 1.414 | 1.411 | 1.413 | 1.413 | 1.413 | 1.414 | 1.415 | 1.414 | 1.414 | 1.413 | 1.414 |
| CB4 | 1.415 | 1.415 | 1.413 | 1.411 | 1.413 | 1.410 | 1.415 | 1.416 | 1.416 | 1.419 | 1.418 | 1.418 |
| CB5 | 1.414 | 1.403 | 1.414 | 1.415 | 1.416 | 1.416 | 1.418 | 1.418 | 1.420 | 1.421 | 1.418 | 1.416 |
| CB6 | 1.414 | 1.415 | 1.413 | 1.414 | 1.413 | 1.413 | 1.414 | 1.414 | 1.414 | 1.416 | 1.415 | 1.415 |
| CB7 | 1.411 | 1.413 | 1.412 | 1.412 | 1.411 | 1.411 | 1.413 | 1.414 | 1.413 | 1.414 | 1.413 | 1.415 |
| CB8 | 1.418 | 1.418 | 1.418 | 1.419 | 1.418 | 1.417 | 1.417 | 1.418 | 1.417 | 1.417 | 1.415 | 1.416 |
| CB9 | 1.417 | 1.417 | 1.418 | 1.417 | 1.418 | 1.416 | 1.417 | 1.416 | 1.415 | 1.416 | 1.413 | 1.413 |
| CB10 | 1.411 | 1.409 | 1.415 | 1.413 | 1.417 | 1.415 | 1.417 | 1.412 | 1.412 | 1.413 | 1.413 | 1.412 |
| CB11 | 1.418 | 1.418 | 1.417 | 1.417 | 1.417 | 1.416 | 1.417 | 1.417 | 1.417 | 1.417 | 1.416 | 1.416 |
| CB12 | 1.417 | 1.418 | 1.418 | 1.419 | 1.418 | 1.417 | 1.418 | 1.419 | 1.419 | 1.420 | 1.416 | 1.417 |
| CB13 | 1.416 | 1.416 | 1.416 | 1.416 | 1.416 | 1.415 | 1.416 | 1.418 | 1.419 | 1.420 | 1.417 | 1.418 |
| CB14 | 1.415 | 1.416 | 1.416 | 1.416 | 1.416 | 1.414 | 1.415 | 1.414 | 1.415 | 1.416 | 1.415 | 1.417 |
| CB15 | 1.413 | 1.412 | 1.409 | 1.409 | 1.410 | 1.411 | 1.413 | 1.416 | 1.415 | 1.415 | 1.414 | 1.415 |
| CB16 | 1.417 | 1.417 | 1.418 | 1.418 | 1.417 | 1.415 | 1.416 | 1.417 | 1.417 | 1.418 | 1.416 | 1.414 |
| CB17 | 1.418 | 1.416 | 1.416 | 1.413 | 1.416 | 1.414 | 1.415 | 1.416 | 1.413 | 1.416 | 1.415 | 1.416 |
| CB18 | 1.415 | 1.416 | 1.417 | 1.417 | 1.416 | 1.415 | 1.416 | 1.417 | 1.415 | 1.417 | 1.415 | 1.415 |
| CB19 | 1.417 | 1.418 | 1.418 | 1.418 | 1.417 | 1.415 | 1.416 | 1.416 | 1.417 | 1.419 | 1.417 | 1.417 |
| CB20 | 1.417 | 1.418 | 1.416 | 1.418 | 1.419 | 1.417 | 1.418 | 1.419 | 1.420 | 1.421 | 1.418 | 1.419 |
| CB21 | 1.413 | 1.414 | 1.415 | 1.414 | 1.414 | 1.435 | 1.413 | 1.411 | 1.414 | 1.414 | 1.412 | 1.413 |
| CB22 | 1.414 | 1.414 | 1.411 | 1.414 | 1.411 | 1.411 | 1.414 | 1.414 | 1.412 | 1.413 | 1.413 | 1.416 |
| CB23 | 1.412 | 1.415 | 1.415 | 1.416 | 1.417 | 1.415 | 1.416 | 1.417 | 1.414 | 1.415 | 1.414 | 1.415 |
| CB24 | 1.416 | 1.416 | 1.416 | 1.417 | 1.416 | 1.414 | 1.415 | 1.415 | 1.411 | 1.413 | 1.414 | 1.414 |
| CB25 | 1.414 | 1.415 | 1.414 | 1.415 | 1.414 | 1.413 | 1.415 | 1.415 | 1.415 | 1.416 | 1.414 | 1.415 |
| CB26 | 1.417 | 1.418 | 1.418 | 1.418 | 1.418 | 1.416 | 1.418 | 1.418 | 1.419 | 1.421 | 1.418 | 1.417 |
| CB27 | 1.414 | 1.414 | 1.410 | 1.412 | 1.411 | 1.411 | 1.414 | 1.415 | 1.413 | 1.397 | 1.413 | 1.413 |
| CB28 | 1.414 | 1.414 | 1.414 | 1.413 | 1.412 | 1.412 | 1.413 | 1.412 | 1.414 | 1.415 | 1.415 | 1.417 |
| CB29 | 1.417 | 1.417 | 1.417 | 1.418 | 1.415 | 1.412 | 1.408 | 1.411 | 1.409 | 1.412 | 1.412 | 1.413 |

Table 5. Aggregate resilience scores Q_i of banks for each year from 2013-2024. (Source: Authors' Computation)

In contrast, several banks show persistent lower rankings, indicating relatively weaker resilience. For instance, Bank of India (CB3), Central Bank of India (CB7) and Dhanlaxmi Bank Ltd. (CB10), UCO Bank (CB27) frequently appeared in the lower ranks. This indicates continuous structural or performance challenges. These banks also exhibit higher ranking divergence reflecting instability in their resilience over time. On the other hand, Yes Bank Ltd. (CB29) experienced substantial declines in their rankings especially from 2018, indicative of the existence of underlying challenges and different government's correction measures such as AQR and IBC implementations during 2016-2017, as well as interventions with revised Prompt Corrective Action (PCA).

Figure 3 presents the heatmap on normalized resilience score of Q_i across different period. The colour gradient, ranging from darker shades (lower scores) to lighter (higher scores) provides a visual representation of the variation in financial resilience across banks and over time. The colour gradient, ranging from darker shades (lower scores) to lighter shades (higher scores), provides a visual representation of the variation in financial resilience across banks and over time. A noticeable deviation is observed around 2018, where a darker vertical band appears across a large number of banks. This indicates a sector-wide decline in resilience during that year, pointing to the presence of a systemic shock affecting the entire banking system rather than isolated bank-specific issues. This might be manifested from two major events in the Indian financial system e.g., PNB scam and the IL&FS crisis during the year 2018 which significantly affected the entire system.



Figure 3. Heatmap on banks year-wise composite financial resilience scores obtained using MEREC-RAM approach. (Source: Authors' Computation)

Following this period, it shows a gradual return to normal range, reflecting recovery and improved resilience in subsequent

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| CB1 | 0.999 | 0.999 | 0.999 | 0.998 | 0.997 | 0.985 | 0.998 | 0.998 | 0.997 | 0.996 | 0.998 | 0.999 |
| CB2 | 0.998 | 0.998 | 0.997 | 0.998 | 0.997 | 0.985 | 0.997 | 0.997 | 0.996 | 0.997 | 0.998 | 0.997 |
| CB3 | 0.997 | 0.997 | 0.995 | 0.996 | 0.996 | 0.984 | 0.997 | 0.997 | 0.995 | 0.995 | 0.996 | 0.996 |
| CB4 | 0.997 | 0.998 | 0.996 | 0.995 | 0.996 | 0.983 | 0.998 | 0.998 | 0.997 | 0.998 | 1.000 | 0.999 |
| CB5 | 0.997 | 0.989 | 0.997 | 0.997 | 0.998 | 0.986 | 0.999 | 0.999 | 1.000 | 1.000 | 1.000 | 0.998 |
| CB6 | 0.997 | 0.998 | 0.996 | 0.997 | 0.996 | 0.985 | 0.997 | 0.996 | 0.996 | 0.996 | 0.997 | 0.997 |
| CB7 | 0.995 | 0.996 | 0.995 | 0.995 | 0.995 | 0.983 | 0.996 | 0.997 | 0.995 | 0.995 | 0.997 | 0.997 |
| CB8 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.987 | 0.999 | 0.999 | 0.997 | 0.997 | 0.997 | 0.998 |
| CB9 | 0.999 | 0.999 | 1.000 | 0.999 | 0.999 | 0.987 | 0.999 | 0.998 | 0.996 | 0.996 | 0.996 | 0.996 |
| CB10 | 0.995 | 0.994 | 0.998 | 0.996 | 0.999 | 0.986 | 0.999 | 0.995 | 0.994 | 0.994 | 0.996 | 0.995 |
| CB11 | 1.000 | 1.000 | 0.999 | 0.999 | 0.999 | 0.987 | 0.999 | 0.999 | 0.997 | 0.997 | 0.998 | 0.998 |
| CB12 | 0.999 | 1.000 | 1.000 | 1.000 | 1.000 | 0.987 | 1.000 | 0.999 | 0.999 | 0.999 | 0.998 | 0.999 |
| CB13 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 | 0.986 | 0.999 | 0.999 | 0.999 | 0.999 | 0.999 | 0.999 |
| CB14 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 | 0.985 | 0.998 | 0.996 | 0.996 | 0.996 | 0.998 | 0.998 |
| CB15 | 0.996 | 0.996 | 0.993 | 0.994 | 0.994 | 0.983 | 0.996 | 0.998 | 0.996 | 0.995 | 0.997 | 0.998 |
| CB16 | 0.999 | 0.999 | 1.000 | 1.000 | 0.999 | 0.986 | 0.998 | 0.999 | 0.998 | 0.998 | 0.999 | 0.996 |
| CB17 | 1.000 | 0.998 | 0.998 | 0.996 | 0.998 | 0.985 | 0.997 | 0.997 | 0.995 | 0.996 | 0.998 | 0.998 |
| CB18 | 0.998 | 0.999 | 0.999 | 0.999 | 0.999 | 0.986 | 0.998 | 0.998 | 0.996 | 0.997 | 0.998 | 0.997 |
| CB19 | 0.999 | 0.999 | 1.000 | 0.999 | 0.999 | 0.986 | 0.999 | 0.998 | 0.997 | 0.998 | 0.999 | 0.999 |
| CB20 | 0.999 | 0.999 | 0.998 | 1.000 | 1.000 | 0.987 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 | 1.000 |
| CB21 | 0.996 | 0.997 | 0.998 | 0.997 | 0.997 | 1.000 | 0.996 | 0.994 | 0.995 | 0.995 | 0.996 | 0.996 |
| CB22 | 0.997 | 0.997 | 0.995 | 0.997 | 0.994 | 0.983 | 0.997 | 0.996 | 0.994 | 0.994 | 0.997 | 0.998 |
| CB23 | 0.996 | 0.997 | 0.997 | 0.998 | 0.999 | 0.986 | 0.998 | 0.998 | 0.996 | 0.996 | 0.997 | 0.997 |
| CB24 | 0.999 | 0.999 | 0.998 | 0.999 | 0.998 | 0.985 | 0.997 | 0.997 | 0.993 | 0.994 | 0.997 | 0.997 |
| CB25 | 0.997 | 0.998 | 0.997 | 0.998 | 0.997 | 0.985 | 0.998 | 0.997 | 0.996 | 0.996 | 0.997 | 0.997 |
| CB26 | 0.999 | 1.000 | 1.000 | 0.999 | 1.000 | 0.987 | 1.000 | 0.999 | 0.999 | 1.000 | 1.000 | 0.999 |
| CB27 | 0.997 | 0.997 | 0.994 | 0.996 | 0.995 | 0.983 | 0.997 | 0.997 | 0.995 | 0.983 | 0.996 | 0.996 |
| CB28 | 0.997 | 0.997 | 0.997 | 0.996 | 0.995 | 0.984 | 0.996 | 0.995 | 0.995 | 0.996 | 0.998 | 0.998 |
| CB29 | 0.999 | 0.999 | 0.999 | 1.000 | 0.997 | 0.984 | 0.993 | 0.994 | 0.992 | 0.993 | 0.996 | 0.996 |

Table 6. Normalized values of aggregate resilience scores (Q_i). (Source: Estimated by the authors)

years. This pattern highlights the ability of banks to adapt and regain stability after adverse conditions.

After this period, it indicates a gradual recovery back to normal range, which shows that banks have returned to a more stable situation in later years. Interestingly, while most other banks' resilience scores fell significantly, as seen in Fig. 3, the Punjab & Sind Bank (CB21) had the highest ranking in terms of resilience in 2018 (Table 7), which was likely due to a one-off balance-sheet adjustments. Overall, the RAM rankings highlight meaningful improvements in relative resilience and systemic stress, rather than dramatic shifts in the banks' absolute strength.

4.3. Hypotheses Testing

The Mann-Kendall (MK) non-parametric trend test was employed using Eq. (14) to examine both bank-level and sector-level dynamics in composite RAM-based financial resilience scores over the period 2013–2024. First, annual RAM scores for 29 banks were structured as a balanced time series, enabling univariate MK tests for each bank to detect statistically significant monotonic trends. The test statistic S , Kendall's tau (τ), and associated p-values were computed for all banks which allow for classification of resilience trajectories as increasing or decreasing trend.

The Mann-Kendall trend analysis in Fig. 4 demonstrates the upward (increasing) and downward (decreasing) trend in financial resilience, as well as banks with no significant trend or (stable over the period) highlighted from 2013 to 2024. The

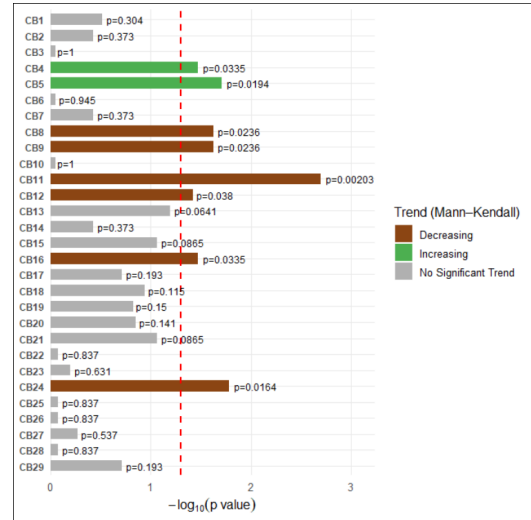


Figure 4. Bank-specific Mann-Kendall Trend Test results (2013–2024). (Source: Authors' Computation)

MEREC-RAM rankings presented in Table 6 capture the relative resilience levels of banks in a particular year, while the Mann-Kendall test captures the dynamics of resilience.

The results reveal that the majority of banks do not exhibit statistically significant trends in their resilience scores

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|
| CB1 | 5 | 7 | 7 | 14 | 18 | 16 | 14 | 10 | 8 | 17 | 8 | 5 |
| CB2 | 15 | 16 | 22 | 16 | 19 | 19 | 22 | 18 | 17 | 12 | 15 | 16 |
| CB3 | 24 | 24 | 26 | 25 | 24 | 22 | 23 | 17 | 20 | 23 | 27 | 24 |
| CB4 | 17 | 17 | 23 | 28 | 22 | 29 | 17 | 13 | 11 | 6 | 3 | 2 |
| CB5 | 22 | 29 | 19 | 18 | 13 | 8 | 4 | 5 | 1 | 1 | 4 | 14 |
| CB6 | 18 | 19 | 24 | 19 | 23 | 21 | 20 | 24 | 18 | 18 | 17 | 20 |
| CB7 | 28 | 26 | 25 | 27 | 26 | 26 | 25 | 22 | 25 | 22 | 22 | 18 |
| CB8 | 3 | 2 | 1 | 2 | 2 | 4 | 5 | 6 | 7 | 11 | 16 | 11 |
| CB9 | 9 | 8 | 5 | 8 | 5 | 5 | 7 | 14 | 14 | 14 | 24 | 28 |
| CB10 | 29 | 28 | 17 | 22 | 10 | 11 | 6 | 27 | 26 | 27 | 26 | 29 |
| CB11 | 2 | 3 | 8 | 9 | 7 | 7 | 8 | 7 | 10 | 10 | 9 | 12 |
| CB12 | 6 | 1 | 2 | 1 | 4 | 3 | 1 | 2 | 3 | 4 | 10 | 6 |
| CB13 | 13 | 15 | 12 | 15 | 16 | 14 | 9 | 3 | 5 | 5 | 5 | 3 |
| CB14 | 16 | 14 | 14 | 13 | 15 | 15 | 15 | 23 | 15 | 15 | 14 | 9 |
| CB15 | 26 | 27 | 29 | 29 | 29 | 27 | 27 | 15 | 13 | 21 | 18 | 15 |
| CB16 | 7 | 9 | 6 | 5 | 6 | 13 | 11 | 8 | 6 | 8 | 7 | 23 |
| CB17 | 1 | 13 | 15 | 23 | 14 | 18 | 18 | 16 | 24 | 16 | 12 | 13 |
| CB18 | 14 | 12 | 9 | 10 | 11 | 9 | 13 | 9 | 12 | 9 | 11 | 19 |
| CB19 | 8 | 5 | 3 | 7 | 8 | 10 | 10 | 12 | 9 | 7 | 6 | 7 |
| CB20 | 4 | 6 | 11 | 3 | 1 | 2 | 2 | 1 | 2 | 3 | 1 | 1 |
| CB21 | 25 | 25 | 16 | 20 | 20 | 1 | 28 | 29 | 21 | 24 | 28 | 27 |
| CB22 | 23 | 22 | 27 | 21 | 28 | 25 | 21 | 25 | 27 | 26 | 23 | 10 |
| CB23 | 27 | 20 | 18 | 12 | 9 | 12 | 12 | 11 | 19 | 19 | 21 | 21 |
| CB24 | 12 | 11 | 13 | 11 | 12 | 17 | 19 | 21 | 28 | 25 | 20 | 22 |
| CB25 | 19 | 18 | 20 | 17 | 21 | 20 | 16 | 19 | 16 | 13 | 19 | 17 |
| CB26 | 10 | 4 | 4 | 6 | 3 | 6 | 3 | 4 | 4 | 2 | 2 | 4 |
| CB27 | 20 | 21 | 28 | 26 | 27 | 28 | 24 | 20 | 23 | 29 | 25 | 26 |
| CB28 | 21 | 23 | 21 | 24 | 25 | 24 | 26 | 26 | 22 | 20 | 13 | 8 |
| CB29 | 11 | 10 | 10 | 4 | 17 | 23 | 29 | 28 | 29 | 28 | 29 | 25 |

Table 7. Year-wise MEREC-based RAM rankings. (Source: Estimated by the authors)

over time. This suggests that financial resilience remains relatively stable for most institutions with no consistent upward or downward trajectory.

However, a subset of banks demonstrates statistically significant trends. Specifically, banks such as CB4 and CB5 exhibit significant improving trends, indicating gradual improvements in resilience over the study period. These results suggest that these banks have strengthened their financial position over time. In contrast, several banks display significant decreasing trends in resilience. Notably, CB8, CB9, CB11, CB12, CB16, and CB24 show statistically significant downward trends, with CB11 exhibiting the strongest decline ($p < 0.01$). This indicates a functional decline in financial resilience for these institutions, which may warrant closer attention from the side of regulatory bodies.

Banks CB4 and CB5 indicate statistically significant upward trends in resilience which align with Financial Resilience Theory and show signs of improvement in solvency, asset quality, efficiency, and profitability. Capital Buffer Theory focuses on the need to maintain sufficient capital and Tier-1 buffers to reduce bank fragility and promote long-term stability. This reflected in the banks with positive trends as well as with the banks showing stable financial resilience throughout the period. Meanwhile, banks that have experienced significant declines that correspond with the theory that weak buffers make banks more vulnerable due to problems with NPAs, inadequate provisioning, and earnings pressure. CB11 display marginally significant declining trend which reflect the lingering effects of

capital erosion, governance challenges, and volatility in profitability. The majority of large public and private sector banks such as CB25, CB1, CB13, CB22, CB25, and so forth, showing no statistically significant trend implies relative stability over the period but limited monotonic improvement in resilience.

The sector-level resilience is further evaluated by constructing annual mean RAM scores, to which separate MK tests are applied. To assess heterogeneity in resilience patterns, the sample was stratified based on ownership structure (public vs. private banks). Both parametric and non-parametric tests were employed to determine whether resilience trajectories differed significantly across subgroups.

Although the initial bank-level Mann–Kendall analysis provides significant evidence on how some banks experienced increasing and decreasing trends in their financial resilience, the Mann–Kendall test for sector mean resilience indicates no statistically significant monotonic trend ($Z = -1.71, p = 0.086$). However, the negative tau (-0.394) suggests a weak declining tendency over the study period. Therefore, the null hypothesis (H_0^1) of no monotonic trend cannot be rejected at the aggregate level.

A Sen’s slope estimator is used to quantify the magnitude and direction of sector-wide change. The estimated slope is visualised in Fig. 5. Initially, a Welch two-sample t-test is conducted on average RAM scores over the study period (2013–2024), which revealed a statistically significant difference between the two groups ($t = 4.64, p < 0.001$). A non-parametric Kruskal–Wallis is additionally performed to ensure robustness. The results confirm a statistically significant difference

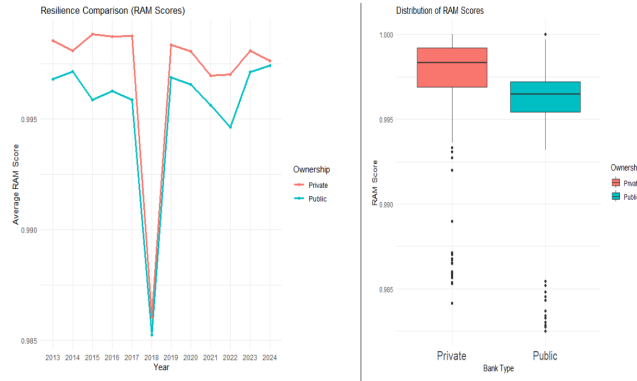


Figure 5. Ownership-Based Heterogeneity Analysis and Sectoral Trend in Financial Resilience. (Source: Authors’ Computation)

in resilience scores, especially between the public and private sector banks ($\chi^2 = 71.096, p < 0.001$). The null hypothesis (H_0) of no difference between public and private banks is rejected, as Welch two-sample t-test and non-parametric tests Kruskal–Wallis reveal statistically significant differences in resilience across ownership groups.

As can be seen in the boxplot (Fig. 5), private banks have a more resilient recovery from the sharp drop around 2018, which is a sign of greater systemic resilience. The different recovery paths of public sector banks (PSBs) and private banks since 2018 show the impact of different governance structures, support for recapitalization, and operational flexibility. Public sector banks received significant recapitalization and governance changes through the EASE and Indradhanush programs. However, they also had to manage a larger amount of legacy non-performing assets. In contrast, private banks usually had more managerial freedom and better profit margin which allow them to recover and adapt more quickly. These differences in structure might caused the varying resilience of each sector after systemic shocks.

These validate that the observed variations in resilience are statistically significant and not an artifact of the MCDM-based ranking framework. The results are also highly consistent with Dynamic Capability Theory, which asserts that firms can maintain superior performance by sensing risks, seizing opportunities, and reconfiguring resources under changing environments[53]. The gradual recovery of the Indian banking sector after the structural change around 2018 also shows a positive adaptive response through a series of balance-sheet adjustments, capital augmentation, and operational restructuring.

4.4. Sensitivity Analysis and Robustness Test

To examine the effect of changes in criteria weighting, a sensitivity analysis is conducted by comparing the baseline MEREC–RAM results with alternative equal-weighting and Entropy-based weighting scenarios. The equal-weighting was implemented by applying 1/11, in which all financial resilience indicators were assigned identical importance 0.0909 (i.e., for 11 criteria), thereby eliminating any data-driven or subjective prioritisation among criteria. Correspondingly, the method entropy is applied to determine objectives which then followed by entropy–RAM rankings.

The study applied additional outranking techniques such as TOPSIS, RATMI, and MARCOS for a robustness test incorporating the MEREC weights. The Kendall’s tau coefficient

is employed to assess the degree of rank concordance among the ranking outcomes obtained from variations in weighting schemes and multiple outranking models. Fig. 6 presents the year-wise p-values of Kendall’s tau coefficient for rank agreement in both the sensitivity analysis and robustness tests.

The consistently high Kendall’s tau coefficients across all years (Fig. 5) indicate that the integrated approach produces stable and reliable rankings. Entropy and MEREC shows near-perfect agreement ($\tau = 0.96 - 1.00$), while Equal Weighting and MEREC ranges from 0.71 to 0.94. This demonstrates that the results are not driven by a specific weighting technique, but rather reflect inherent data structure. Under the robustness test, RAM and TOPSIS (0.79–0.95) show strongest agreement, followed by RAM-MARCOS (0.67–0.89) and RAM-RATMI (0.67–0.81). The absence of significant rank reversals across methods and time reinforces the robustness of the framework.

5. Conclusions

Assessing banks’ financial resilience is vital in emerging economies, where financial systems are characterized by volatility, governance constraints, and heightened exposure to NPAs. Thus, in order to assess the financial resilience Indian commercial banks between 2013 and 2024, this study developed an integrated analytical framework that combines the MEREC objective weighting approach, the RAM-based composite resilience index, and Mann-Kendall trend analysis.

The results showed that the RAM-based resilience rankings are narrowly clustered among banks, indicating the effect of structural convergence brought about by regulatory standardization. The statistical significance tests Kruskal–Wallis verify that the observed differences are meaningful and significant. However, the trend analysis shows that resilience trajectories at the bank level vary significantly. A limited number of banks have statistically significant monotonic trends, but cross-sectional rankings show year-to-year variability for most banks. The lack of a noticeable trend at the sector-level indicates that the Indian banking sector resilience develops through periodic adjustments rather than steady directional improvement. Moreover, while Private sector banks showed greater adaptive capacity and quicker recovery from systemic shocks, public banks were more sensitive to regulatory interventions.

The MEREC–RAM ranking result showed Kotak Mahindra Bank Ltd. and Tamilnad Mercantile Bank Ltd. consistently showed strong resilience across the study period. Meanwhile the CSB Bank Ltd. reflected significant improvement in rankings

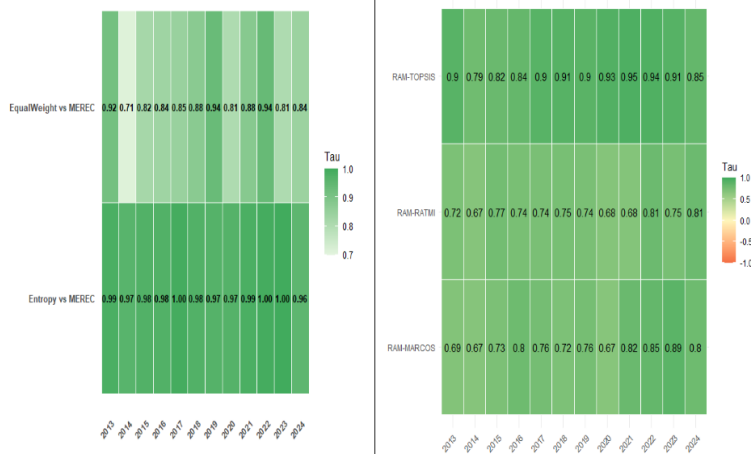


Figure 6. Heatmaps on Kendall's tau (τ) across methods. (Source: Authors' Computation)

from bottom to top ten over the years. Bank of Maharashtra also demonstrated significant improvement in rankings by reaching to the second place during 2024. Conversely, Bank of India, Central Bank of India and Dhanlaxmi Bank Ltd., UCO Bank constantly positioned at the bottom in the rankings. Interestingly, the Mann-kendall trend test showed significant improvement in the resilience of Bank of Maharashtra and CSB Bank Ltd. during the study period. Whereas, City Union Bank Ltd., DCB Bank Ltd., Federal Bank Ltd., HDFC Bank Ltd., Indusind Bank Ltd., and South Indian Bank Ltd. reflected significant decline in their financial resilience. However, other banks demonstrated stable or no significant improvement or deterioration.

This study contributes to Financial Resilience Theory in showing that resilience is non-linear, heterogeneous, and convergent rather than monotonic. These findings are also in line with Institutional Adaptation Theory, which contends that resilience outcomes depend on banks' capacity to adapt to shifting macroeconomic and regulatory conditions. The results are consistent with a convergence-differentiation approach to banking resilience, in which statistically significant performance differences resulting from differences in banks' capacity to adapt, manage risks, and react to changing conditions are contrasted with structural similarity brought about by regulatory frameworks.

The Mann-Kendall analysis shows that banks exhibit distinct resilience trajectories, which have significant managerial and policy significance. From a managerial perspective, the findings suggest that persistent adaptive capability is necessary in addition to maintaining high relative rankings. To achieve long-term resilience, banks must place the utmost importance on proactive risk management, ongoing balance-sheet reconfiguration, and operational effectiveness. Banks with increasing trends demonstrate great adaptive capacity and can serve as benchmarks for best practices, with a continuous emphasis on risk management and capital strengthening. Banks showing deteriorating trends (e.g., CB8, CB9, CB11, CB12, CB16, and CB24) should prioritize strengthening asset quality through stricter credit appraisal, early warning systems, and faster resolution of non-performing assets. Management should improve capital adequacy, liquidity buffers, and risk governance while adopting data-driven monitoring of profitability and operational efficiency. Diversification of loan portfolios and

digital transformation can reduce concentration and operating risks. Regulators may encourage periodic stress testing, enhanced disclosure standards, and corrective action frameworks for vulnerable banks. From a policy perspective, the lack of a broad sector-wide trend indicates that while regulatory changes have stabilized the system, they have not consistently increased resilience.

Although the study makes important contributions, it is limited by its analysis to financial indicators without incorporating macroeconomic or market-based variables. Although the Mann-Kendall test captures monotonic trends but it unable to conduct a complete structural break or regime shifts. Further research could expand on this framework by including macro-financial variables, structural break or panel-based approaches, and identifying causal links between regulatory interventions, adaptive capacities, and banking system resilience.

Ethical Statement

No ethical approval was required for this study, as it did not involve human or animal subjects. The study relied exclusively on secondary data obtained from publicly available and authorized databases and annual reports.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statements

The data supporting the findings of this study are available from the corresponding author upon reasonable request. However, the data are not publicly available due to access restrictions associated with the Prowess-IQ database and institutional data usage policies. Data were obtained from authorized sources

including Prowess-IQ (<https://prowess.cmie.com/>) and annual reports of banks.

Credit authorship contribution statement

Priya Das: Conceptualization; Methodology; Investigation; Data Curation; Formal Analysis; Software; Visualization; Writing – Original Draft Preparation. Subir Kumar Sen: Conceptualization; Supervision; Project Administration; Validation; Visualization; Resources; Writing – Review & Editing.

References

1. F. Salignac, A. Marjolin, R. Reeve, and K. Muir, “Conceptualizing and measuring financial resilience,” *Social Indicators Research*, vol. 145, no. 1, pp. 17–38, 2019, doi: <https://doi.org/10.1007/s11205-019-02100-4>.
2. F. Salignac, J. Hanoteau, and I. Ramia, “Financial resilience: a way forward towards economic development in developing countries,” *Social Indicators Research*, vol. 160, no. 1, pp. 1–33, 2022, doi: <https://doi.org/10.1007/s11205-021-02793-6>.
3. S. K. Nkundabanyanga, E. Mugumya, I. Nalukenge, M. Muhwezi, and G. M. Najjemba, “Firm characteristics, innovation, financial resilience and survival of financial institutions,” *Journal of Accounting in Emerging Economies*, vol. 10, no. 1, pp. 48–73, 2020, doi: <https://doi.org/10.1108/JAEE-08-2018-0094>.
4. F. S. Hamid, Y. J. Loke, and P. N. Chin, “Determinants of financial resilience: insights from an emerging economy,” *Journal of social and economic development*, vol. 25, no. 2, pp. 479–499, 2023, doi: <https://doi.org/10.1007/s40847-023-00239-y>.
5. A. A. Tinta, I. M. Ouédraogo, and R. M. Al-Hassan, “The micro determinants of financial inclusion and financial resilience in africa,” *African Development Review*, vol. 34, no. 2, pp. 293–306, 2022, doi: <https://doi.org/10.1111/1467-8268.12636>.
6. A. Das and S. Ghosh, “Financial deregulation and profit efficiency: A nonparametric analysis of indian banks,” *Journal of Economics and Business*, vol. 61, no. 6, pp. 509–528, 2009, doi: <https://doi.org/10.1016/j.jeconbus.2009.07.003>.
7. S. Kumar and R. Gulati, “Did the global financial crisis alter the competitive conditions in the indian banking industry?” *Applied Economics Letters*, vol. 26, no. 10, pp. 857–865, 2019, doi: <https://doi.org/10.1080/13504851.2018.1502865>.
8. N. Mohan and M. Irfan, “Applying ai & topsis-mcdm tool in evaluating top five private indian bank performances,” in *Applications of Block Chain technology and Artificial Intelligence: Lead-ins in Banking, Finance, and Capital Market*. Springer, 2024, pp. 291–303, doi: https://doi.org/10.1007/978-3-031-47324-1_15.
9. G. Caprio, *Banking on crises: expensive lessons from recent financial crises*. World Bank, Development Research Group, Finance, 1998, no. 1979.
10. A. Bhattacharyya, C. K. Lovell, and P. Sahay, “The impact of liberalization on the productive efficiency of indian commercial banks,” *European Journal of operational research*, vol. 98, no. 2, pp. 332–345, 1997, doi: [https://doi.org/10.1016/S0377-2217\(96\)00351-7](https://doi.org/10.1016/S0377-2217(96)00351-7).
11. S. Akhtar, S. N. Azmi, P. A. Khan, A. A. Jan, and Z. Ansari, “Unveiling the financial landscape: analyzing profitability, productivity, and efficiency of banks in an emerging economy using the camels framework and panel analysis,” *Cogent Business & Management*, vol. 11, no. 1, p. 2399747, 2024, doi: <https://doi.org/10.1080/23311975.2024.2399747>.
12. A. Sharma, “Incomplete reform or opportunity: the role of the banking sector in the credit transmission mechanism in india,” *Journal of Economic Policy Reform*, vol. 11, no. 4, pp. 273–288, 2008, doi: <https://doi.org/10.1080/17487870802567315>.
13. B. Eichengreen and P. Gupta, “The financial crisis and indian banks: survival of the fittest?” *Journal of International Money and Finance*, vol. 39, pp. 138–152, 2013, doi: <https://doi.org/10.1016/j.jimonfin.2013.06.022>.
14. H. Fujii, S. Managi, and R. Matousek, “Indian bank efficiency and productivity changes with undesirable outputs: A disaggregated approach,” *Journal of banking & finance*, vol. 38, pp. 41–50, 2014, doi: <https://doi.org/10.1016/j.jbankfin.2013.09.022>.
15. K. Srinivasan, K. Ramesh, K. Gunasekaran, and K. Sivasubramanian, “Reforms in indian banking sector: a paradigm shift in growth and financial inclusion in india,” in *Technology-Driven Business Innovation: Unleashing the Digital Advantage, Volume 1*. Springer, 2024, pp. 433–439, doi: https://doi.org/10.1007/978-3-031-51997-0_36.
16. N. Shikha and I. Kapsis, “Bank crisis management and resolution after svb and credit suisse: Perspectives from india and the european union,” *International Insolvency Review*, vol. 33, no. 1, pp. 55–88, 2024, doi: <https://doi.org/10.1002/ir.1516>.
17. A. Nasim, G. Downing, and M. A. Nasir, “The role of uncertainty, regulatory and economic environment and quantitative tightening in banks’ performance,” *International Journal of Finance & Economics*, vol. 31, no. 1, pp. 46–69, 2026, doi: <https://doi.org/10.1002/ijfe.3128>.
18. K. D. Hanumantu, V. Worlikar, and S. Narayanaswami, “The punjab national bank scam: Ethics versus robust processes,” *Journal of Public Affairs*, vol. 19, no. 4, p. e1952, 2019, doi: <https://doi.org/10.1002/pa.1952>.
19. J. Truby, R. Brown, and A. Dahdal, “Banking on ai: mandating a proactive approach to ai regulation in the financial sector,” *Law and Financial Markets Review*, vol. 14, no. 2, pp. 110–120, 2020, doi: <https://doi.org/10.1080/17521440.2020.1760454>.
20. A. Sotoudeh-Anvari, “Root assessment method (ram): A novel multi-criteria decision making method and its applications in sustainability challenges,” *Journal of Cleaner Production*, vol. 423, p. 138695, 2023, doi: <https://doi.org/10.1016/j.jclepro.2023.138695>.
21. —, “Root assessment method (ram) under neutrosophic environment,” in *Neutrosophic Paradigms: Advancements in Decision Making and Statistical Analysis: Neutrosophic Principles for Handling Uncertainty*. Springer, 2025, pp. 123–138, doi: https://doi.org/10.1007/978-3-031-78505-4_6.
22. M. Keshavarz-Ghorabae, M. Amiri, E. K. Zavadskas, Z. Turskis, and J. Antucheviciene, “Determination of objective weights using a new method based on the removal effects of criteria (mrec),” *Symmetry*, vol. 13, no. 4, p. 525, 2021, doi: <https://doi.org/10.3390/sym13040525>.

23. M. S. Tahir and D. W. Richards, "A systematic literature review of financial resilience: antecedents, consequences and future research agenda," *Journal of Financial Regulation and Compliance*, 2025, doi: <https://doi.org/10.1108/JFRC-10-2024-0204>.
24. L. Klapper and A. Lusardi, "Financial literacy and financial resilience: Evidence from around the world," *Financial Management*, vol. 49, no. 3, pp. 589–614, 2020, doi: <https://doi.org/10.1111/fima.12283>.
25. A. Lusardi, A. Hasler, and P. J. Yakoboski, "Building up financial literacy and financial resilience," *Mind & Society*, vol. 20, no. 2, pp. 181–187, 2021, doi: <https://doi.org/10.1007/s11299-020-00246-0>.
26. C. Jansson, "Financial resilience: the role of financial balance, profitability, and ownership," in *The Resilience Framework: Organizing for Sustained Viability*. Springer, 2017, pp. 111–131, doi: https://doi.org/10.1007/978-981-10-5314-6_7.
27. A. Sreenivasan and M. Suresh, "Readiness of financial resilience in start-ups," *Journal of Safety Science and Resilience*, vol. 4, no. 3, pp. 241–252, 2023, doi: <https://doi.org/10.1016/j.jnlssr.2023.02.004>.
28. R. L. Clark and O. S. Mitchell, "Americans' financial resilience during the pandemic," *Financial Planning Review*, vol. 5, no. 2-3, p. e1140, 2022, doi: <https://doi.org/10.1002/cfp2.1140>.
29. G. M. Markman and M. Venzin, "Resilience: Lessons from banks that have braved the economic crisis—and from those that have not," *International Business Review*, vol. 23, no. 6, pp. 1096–1107, 2014, doi: <https://doi.org/10.1016/j.ibusrev.2014.06.013>.
30. G. O. Danisman, E. Demir, and A. Zaremba, "Financial resilience to the covid-19 pandemic: The role of banking market structure," *Applied Economics*, vol. 53, no. 39, pp. 4481–4504, 2021, doi: <https://doi.org/10.1080/00036846.2021.1904118>.
31. T. Papadimitriou, P. Gogas, and A. Agrapetidou, "The resilience of the us banking system," *International Journal of Finance & Economics*, vol. 27, no. 3, pp. 2819–2835, 2022, doi: <https://doi.org/10.1002/ijfe.2300>.
32. C. Cantú, R. Lobato, C. López, and F. López-Gallo, "A loan-level analysis of financial resilience in mexico," *Journal of Banking & Finance*, vol. 135, p. 105951, 2022, doi: <https://doi.org/10.1016/j.jbankfin.2020.105951>.
33. S. Alam, S. K. Das, U. R. Dipa, and S. Z. Hossain, "Predicting financial distress through ownership pattern: dynamics of financial resilience of bangladesh," *Future Business Journal*, vol. 10, no. 1, p. 91, 2024, doi: <https://doi.org/10.1186/s43093-024-00379-5>.
34. E. Daadmehr, "Workplace sustainability or financial resilience? composite-financial resilience index," *Risk management*, vol. 26, no. 2, p. 7, 2024, doi: <https://doi.org/10.1057/s41283-023-00139-9>.
35. Y. Chen and C. Sun, "A new method for measuring financial resilience," *Economics Letters*, vol. 242, p. 111883, 2024, doi: <https://doi.org/10.1016/j.econlet.2024.111883>.
36. E. K. Zavadskas, Z. Turskis, J. Antucheviciene, and A. Zakarevicius, "Optimization of weighted aggregated sum product assessment," *Elektronika ir elektrotechnika*, vol. 122, no. 6, pp. 3–6, 2012, doi: <https://doi.org/10.5755/j01.eee.122.6.1810>.
37. S. Gupta, M. Mathew, S. Gupta, and V. Dawar, "Benchmarking the private sector banks in india using mcdm approach," *Journal of Public Affairs*, vol. 21, no. 2, p. e2409, 2021, doi: <https://doi.org/10.1002/pa.2409>.
38. S. Gupta, M. Mathew, G. Syal, and J. Jain, "A hybrid mcdm approach for evaluating the financial performance of public sector banks in india," *International Journal of Business Excellence*, vol. 24, no. 4, pp. 481–501, 2021, doi: <https://doi.org/10.1504/IJBEX.2021.117648>.
39. P.-H. Nguyen, J.-F. Tsai, Y.-C. Hu, and G. V. Ajay Kumar, "A hybrid method of mcdm for evaluating financial performance of vietnamese commercial banks under covid-19 impacts," in *Shifting economic, financial and banking paradigm: New systems to encounter COVID-19*. Springer, 2021, pp. 23–45, doi: https://doi.org/10.1007/978-3-030-79610-5_2.
40. A. Karbassi Yazdi, C. Spulbar, T. Hanne, and R. Birau, "Ranking performance indicators related to banking by using hybrid multicriteria methods in an uncertain environment: A case study for iran under covid-19 conditions," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 166–180, 2022, doi: <https://doi.org/10.1080/21642583.2022.2052996>.
41. U. Ünlü, N. Yalçın, and N. Avşarlıgil, "Analysis of efficiency and productivity of commercial banks in turkey pre-and during covid-19 with an integrated mcdm approach," *Mathematics*, vol. 10, no. 13, p. 2300, 2022, doi: <https://doi.org/10.3390/math10132300>.
42. Y. A. Ünvan and C. Ergenç, "Financial performance analysis with the fuzzy copras and entropy-copras approaches," *Computational Economics*, vol. 59, no. 4, pp. 1577–1605, 2022, doi: <https://doi.org/10.1007/s10614-021-10143-4>.
43. P. Wanke, M. A. K. Azad, A. K. Yazdi, F. R. Birau, and C. M. Spulbar, "Revisiting camels rating system and the performance of asean banks: a comprehensive mcdm/z-numbers approach," *IEEE Access*, vol. 10, pp. 54 098–54 109, 2022, doi: <https://doi.org/10.1109/ACCESS.2022.3171339>.
44. H. R. Sama, S. V. K. Kosuri, and S. Kalvakolanu, "Evaluating and ranking the indian private sector banks—a multi-criteria decision-making approach," *Journal of Public Affairs*, vol. 22, no. 2, p. e2419, 2022, doi: <https://doi.org/10.1002/pa.2419>.
45. P. Kumar and D. Sharma, "Prioritising the financial performance of indian private sector banks by a hybrid mcdm approach," *International Journal of Process Management and Benchmarking*, vol. 16, no. 4, pp. 490–511, 2024, doi: <https://doi.org/10.1504/IJPMB.2024.137145>.
46. Ö. Karadağ Ak, A. Hazar, and Ş. Babuşcu, "Evaluation of the financial performance of development and investment banks with entropy-based aras method," *Macroeconomics and Finance in Emerging Market Economies*, vol. 18, no. 2, pp. 441–461, 2025, doi: <https://doi.org/10.1080/17520843.2022.2035523>.
47. Ö. Işık, M. Shabir, G. Demir, A. Puska, and D. Pamucar, "A hybrid framework for assessing pakistani commercial bank performance using multi-criteria decision-making," *Financial Innovation*, vol. 11, no. 1, p. 38, 2025, doi: <https://doi.org/10.1186/s40854-024-00728-x>.
48. J. Zahedi, M. Salehi, and M. Moradi, "Identifying and classifying the contributing factors to financial resilience," *foresight*, vol. 24, no. 2, pp. 177–194, 2022, doi: <https://doi.org/10.1108/FS-10-2020-0102>.
49. Z. Liu, J.-K. Chen, and J. J. Xiao, "Financial resilience: a scoping review, conceptual synthesis and

- theoretical framework,” *International Journal of Bank Marketing*, vol. 43, no. 7, pp. 1541–1576, 2025, doi: <https://doi.org/10.1108/IJBM-12-2024-0735>.
50. T. Jokipii and A. Milne, “Bank capital buffer and risk adjustment decisions,” *Journal of Financial Stability*, vol. 7, no. 3, pp. 165–178, 2011, doi: <https://doi.org/10.1016/j.jfs.2010.02.002>.
 51. D. Corbae and P. D’Erasmus, “Capital buffers in a quantitative model of banking industry dynamics,” *Econometrica*, vol. 89, no. 6, pp. 2975–3023, 2021, doi: <https://doi.org/10.3982/ECTA16930>.
 52. C. D. Carroll, R. E. Hall, and S. P. Zeldes, “The buffer-stock theory of saving: Some macroeconomic evidence,” *Brookings papers on economic activity*, vol. 1992, no. 2, pp. 61–156, 1992, doi: <https://doi.org/10.2307/2534582>.
 53. D. J. Teece, G. Pisano, and A. Shuen, “Dynamic capabilities and strategic management,” *Strategic management journal*, vol. 18, no. 7, pp. 509–533, 1997, doi: [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)](https://doi.org/10.1002/(SICI)1097-0266(199708)).
 54. M. M. H. Chowdhury and M. Quaddus, “Supply chain resilience: conceptualization and scale development using dynamic capability theory,” *International journal of production economics*, vol. 188, pp. 185–204, 2017, doi: <https://doi.org/10.1016/j.ijpe.2017.03.020>.
 55. M. Doumpos and C. Zopounidis, “A multicriteria decision support system for bank rating,” *Decision support systems*, vol. 50, no. 1, pp. 55–63, 2010, doi: <https://doi.org/10.1016/j.dss.2010.07.002>.
 56. R. Ginevičius and A. Podvieszko, “The evaluation of financial stability and soundness of lithuanian banks,” *Economic research-Ekonomska istraživanja*, vol. 26, no. 2, pp. 191–208, 2013, doi: <https://doi.org/10.1080/1331677X.2013.11517616>.
 57. B. Gavurova, J. Belas, K. Kocisova, and T. Kliestik, “Comparison of selected methods for performance evaluation of czech and slovak commercial banks,” *Journal of Business Economics and Management*, vol. 18, no. 5, pp. 852–876, 2017, doi: <https://doi.org/10.3846/16111699.2017.1371637>.
 58. M. Dash, “A model for bank performance measurement integrating multivariate factor structure with multi-criteria promethee methodology,” *Asian Journal of Finance & Accounting*, vol. 9, no. 1, pp. 310–332, 2017, doi: <https://doi.org/10.5296/ajfa.v9i1.11073>.
 59. C. Ayadurai and R. Eskandari, “Bank soundness: a pls-sem approach,” in *Partial least squares structural equation modeling: Recent advances in banking and finance*. Springer, 2018, pp. 31–52, doi: https://doi.org/10.1007/978-3-319-71691-6_2.
 60. I. Marjanović and Ž. Popović, “Mcdm approach for assessment of financial performance of serbian banks,” in *Business performance and financial institutions in Europe: Business models and value creation across European industries*. Springer, 2020, pp. 71–90, doi: https://doi.org/10.1007/978-3-030-57517-5_5.
 61. J. Reig-Mullor, J. M. Brotons-Martinez, and M. E. Sansalvador-Selles, “A novel approach to improve the bank ranking process: an empirical study in spain,” *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 5, pp. 5323–5331, 2020, doi: <https://doi.org/10.3233/JIFS-179626>.
 62. M. A. Bushashe, “Determinants of private banks performance in ethiopia: A partial least square structural equation model analysis (pls-sem),” *Cogent Business & Management*, vol. 10, no. 1, p. 2174246, 2023, doi: <https://doi.org/10.1080/23311975.2023.2174246>.
 63. V. Sharma, M. Gupta, and K. Jangir, “Exploring the impact of risk factors on profitability in commercial banking in india: a pls-sem analysis approach,” 2024, doi: <https://doi.org/10.1108/978-1-83753-734-120241007>.
 64. S. S. Goswami, S. K. Mohanty, and D. K. Behera, “Selection of a green renewable energy source in india with the help of merec integrated piv mcdm tool,” *Materials today: proceedings*, vol. 52, pp. 1153–1160, 2022, doi: <https://doi.org/10.1016/j.matpr.2021.11.019>.
 65. S. Kumar, P. Ahijith Kumar, K. Bharati, L. Patnaik, S. Ranjan Maity, and M. Lepicka, “Coating material selection for bulk metal forming dies: A merec-integrated approach with multiple mcdm methods,” *International Journal on Interactive Design and Manufacturing (IJI-DeM)*, vol. 19, no. 6, pp. 4055–4070, 2025, doi: <https://doi.org/10.1007/s12008-024-01983-z>.
 66. I. M. Hezam, A. M. Ali, K. Sallam, I. A. Hameed, A. Foul, and M. Abdel-Basset, “An extension of root assessment method (ram) under spherical fuzzy framework for optimal selection of electricity production technologies toward sustainability: a case study,” *International Journal of Energy Research*, vol. 2024, no. 1, p. 7985867, 2024, doi: <https://doi.org/10.1155/2024/7985867>.
 67. T. Van Dua, D. D. Trung, N. T. P. Giang, and D. Van Duc, “Comparison of two methods: Ram and aroman,” in *International Conference on Sustainability and Emerging Technologies for Smart Manufacturing*. Springer, 2024, pp. 727–735, doi: https://doi.org/10.1007/978-981-97-7083-0_73.
 68. A. Shekhovtsov, M. Gandorc, R. Pawlakb, and W. Sařabuna, “A novel rancom-ram-based framework for city assessment based on cost of living,” *Procedia Computer Science*, vol. 270, pp. 5776–5786, 2025, doi: <https://doi.org/10.1016/j.procs.2025.10.046>.