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Identification of Key Risk Indicators in the Perspectives of the Sustainable Balanced Scorecard for Performance Evaluation of Sepah Bank Branches in Qazvin Province and Determination of Causal Relationships Using Fuzzy DEMATEL

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ABSTRACT

The main objective of the present study was to identify the key risk indicators within the perspectives of the sustainable Balanced Scorecard for evaluating the performance of Sepah Bank branches in Qazvin Province and to determine causal relationships using the fuzzy DEMATEL method. The statistical population consisted of 460 employees of Sepah Bank in the Qazvin region. In fact, all Sepah Bank personnel, including staff in both operational and administrative units, constituted the study population. A purposive sampling method was used. From an operational standpoint and in terms of data collection, the necessary field investigations were conducted by attending the organization, examining the prevailing conditions and regulations, and exploring feasible information-gathering procedures. Given that the research was case-based, the first step involved examining the current methods and conditions governing the identification of risk-generating indicators in the organization under study, as well as the variables and indicators affecting this area, in order to obtain an overall understanding of the organization's background on this subject. The data collection tools consisted of note-taking from previous studies and a DEMATEL questionnaire administered in the field. Considering the nature of the topic, a questionnaire was used to collect the data. The information obtained from experts was categorized to determine, from among the indicators extracted from scientific articles, those most suitable for the present research. The experts' opinions regarding each alternative were then aggregated to produce a single consolidated judgment. After collecting the required data, MATLAB and EXCEL software programs were used at various stages to perform the necessary computations. In addition, SPSS software was employed to examine the regression equation. Initially, the key risk indicators were identified across the five dimensions of the extended Balanced Scorecard framework for performance evaluation. Subsequently, using the DEMATEL method, the causal relationships among the five perspectives were analyzed. The results indicated that the sustainability-related perspective, based on the DEMATEL output, functioned as an independent causal perspective influencing the other dimensions; therefore, sustainability-related risks were identified as influential factors affecting other components and the overall performance of the bank. In response to this research question, it is emphasized that based on the results of the fuzzy network analysis method and insights from banking experts, 30 quantitative and qualitative risks were identified in accordance with the perspectives of the Balanced Scorecard.

Keywords: performance evaluation, risk, green Balanced Scorecard, multi-criteria decision-making, VIKOR, fuzzy, DEMATEL, network analysis method, VIKOR.

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Introduction

Credit risk management has become one of the core pillars of banking stability in an environment characterized by rising financial complexity, macroeconomic uncertainty, and growing regulatory scrutiny (1). In both advanced and emerging economies, the accumulation of non-performing loans, contagion effects across institutions, and feedback loops between bank credit, inflation, and default risk have underscored the need for robust and forward-looking risk management frameworks (2). Monetary policy transmission interacts closely with banks' capital structure and risk-taking behavior, such that shifts in policy rates and liquidity conditions can alter credit risk profiles and profitability, especially in bank-dominated financial systems (3). Against this backdrop, the design of integrated credit risk management models that combine micro-level risk assessment with macro-financial constraints has emerged as a strategic priority for regulators, bank managers, and policymakers alike (4).

In recent years, extensive empirical and theoretical work has analyzed how credit risk and its management practices influence the financial performance of banks across different jurisdictions. Evidence from South Asian commercial banks shows that the quality of credit risk management and bank-specific factors such as capitalization, liquidity, and efficiency significantly shape profitability and resilience (5). Similar findings have been reported for deposit money banks, where sound credit risk practices contribute to sustained returns and reduced earnings volatility (6). Studies on Tanzanian commercial banks further confirm that the quality of credit risk management processes—ranging from risk identification to monitoring and mitigation—has a measurable impact on financial outcomes, highlighting the strategic nature of risk governance in competitive markets (7). In the context of economic crises, relationship banking, collateral structures, and macroeconomic shocks interact to drive credit risk in small and medium-sized enterprises, illustrating the importance of institutional and relational dimensions in risk assessment (8).

Within the Iranian banking system, credit risk has been recognized as a central driver of bank performance, capital adequacy, and lending capacity. Studies on agricultural and specialized banks indicate that deficiencies in credit risk management can impair lending performance and reduce the effectiveness of financial intermediation, particularly in priority sectors such as agriculture and rural development (9). At the same time, comprehensive analyses of credit risk in economic sectors—including industry, agriculture, services, and housing—show that sectoral heterogeneity in default patterns and cyclical sensitivity must be incorporated into bank-wide risk models (10). More recent work on credit risk and capital adequacy in listed Iranian banks documents that bank size, ownership structure, and governance arrangements shape risk-taking behavior and capital buffers, thereby influencing systemic stability (11, 12). These findings reinforce the need for integrated, data-driven approaches that can align risk management practices with regulatory requirements and market conditions (13).

Corporate governance has also emerged as a critical antecedent of credit risk and financial distress. Evidence from Iraqi banks suggests that governance mechanisms—such as board independence, transparency, and risk committee effectiveness—play a pivotal role in constraining excessive risk-taking and reducing the probability of distress (14). Risk-based supervision frameworks, which shift regulatory attention from purely compliance-oriented checklists to the underlying risk profile of institutions, have been proposed as a way to better align supervisory intensity with banks' actual exposures (15). In the Iranian context, grounded-theory studies have yielded conceptual models of risk-based supervision for banks and credit institutions, emphasizing the interplay between regulatory expectations, internal control systems, and market discipline (15). These approaches resonate with international work on optimal bank regulation that explicitly accounts for both credit and run risk, showing that regulatory tools must be designed to manage solvency and liquidity dimensions simultaneously (4).

The rise of financial technology (fintech) has further transformed the landscape of credit risk management. Studies on banks listed on the Tehran Stock Exchange indicate that fintech adoption can improve financial performance by enhancing credit assessment, risk monitoring, and transaction efficiency, provided that the associated credit risks are appropriately managed (16, 17). Other research suggests that fintech can reduce credit risk and improve bank performance through enhanced data analytics and real-time monitoring of borrower behavior, particularly when integrated with traditional risk management systems (18). Innovations such as blockchain-based credit risk management systems promise greater transparency, tamper-resistant records, and automated enforcement of collateral and covenants, thereby reducing operational and informational asymmetries in lending relationships (19). At the same time, systems-thinking approaches to comprehensive risk management models emphasize that technological innovation must be embedded within a broader architecture that captures feedback loops, delays, and nonlinearities in the banking system (20).

Parallel to technological developments, artificial intelligence (AI) and machine-learning techniques have increasingly been applied to credit risk modeling. Meta-heuristic AI approaches have been used to design credit risk models for Iranian banks, demonstrating that evolutionary algorithms and intelligent search procedures can enhance classification accuracy and optimize risk-return trade-offs (21). Hybrid models that integrate support vector machines with genetic algorithms have shown improved performance in predicting default probabilities and segmenting bank customers by risk level (22). At a macro level, AI-driven models can also support scenario analysis of credit, inflation, and default risk interactions over long horizons, providing central banks and regulators with tools for stress testing and macro-prudential policy design (2). However, these approaches require high-quality data, robust validation, and careful governance to avoid model risk and unintended procyclical effects (1).

Environmental, social, and governance (ESG) considerations are increasingly being integrated into credit risk assessment, especially in light of climate transition risks. Government-initiated environmental credit rating schemes link firms' environmental performance and climate transition exposure to their credit profiles, thereby influencing banks' lending decisions and portfolio composition (23). In parallel, evidence from China indicates that local ESG ratings can provide superior information for credit risk assessment relative to more generic global scores, particularly when assessing default distance and long-term solvency (24). These developments suggest that traditional credit risk models must be expanded to incorporate climate-related and ESG-driven risk factors, especially for banks that are highly exposed to carbon-intensive sectors or operate in jurisdictions that are implementing green finance policies (23, 24).

Methodologically, the literature has witnessed a growing reliance on multi-criteria decision-making (MCDM) and data envelopment analysis (DEA) to evaluate risk and performance in complex environments. Grey multi-criteria decision-making has been used to assess safety risk in the construction industry, demonstrating how linguistic and uncertain information can be systematically integrated into risk evaluation frameworks (25). Fuzzy DEA models have been proposed to measure efficiency when inputs and outputs are subject to vagueness or imprecision, offering a flexible tool for benchmarking banks and other decision-making units under risk (26). In addition, integrated models that combine the sustainability balanced scorecard (SBSC) with MCDM methods have been used to evaluate the performance of oil-producing companies, illustrating how financial, customer, internal process, learning, and sustainability dimensions can be captured simultaneously using linguistic variables and expert judgments (27). These approaches are particularly relevant for banking, where multiple stakeholders, conflicting objectives, and non-quantifiable risk dimensions must be considered in a holistic manner (27, 28).

The balanced scorecard and its sustainability-oriented extensions have therefore emerged as attractive frameworks for combining traditional financial risk measures with operational, customer, learning, and environmental indicators. Studies of e-supply chain management performance measurement show that the balanced scorecard can capture multi-stage diffusion effects and link operational performance with strategic outcomes (28). When enriched with sustainability perspectives and linked to MCDM techniques, the balanced scorecard can serve as a platform for integrating credit risk, liquidity risk, operational risk, and environmental risk into a unified assessment architecture (27). In parallel, books and policy reports on credit risk management, bank regulation, and risk-based supervision offer conceptual frameworks that stress the importance of aligning risk appetite, regulatory capital, and business strategy in a coherent manner (1, 13, 15).

At the level of national banking systems, several studies have examined how credit risk and its management influence the performance of listed banks in capital markets. Research on the Tehran Stock Exchange indicates that credit risk, capital adequacy, bank size, and ownership structure jointly determine banks' financial stability and capacity to absorb shocks (11, 12). Other work has analyzed the effect of fintech adoption on financial efficiency and credit risk in these banks, showing that digital innovations can both mitigate and amplify risk depending on governance quality and implementation strategies (16-18). Beyond Iran, empirical studies in Indonesia and other emerging markets have linked monetary policy, capital structure, and credit risk to bank profitability, underscoring the need for context-sensitive models that can account for country-specific regulatory, macroeconomic, and institutional features (3, 6, 7).

Despite this rich body of research, several gaps remain. Much of the existing literature focuses either on micro-level modeling of credit risk using statistical or AI-based techniques, or on macro-prudential and regulatory perspectives that emphasize capital adequacy and systemic stability, with relatively few studies attempting to integrate these dimensions into a comprehensive, systems-based framework (2, 20). Furthermore, although MCDM and DEA methods have been used extensively in other industries, their application to banking risk management—particularly in conjunction with sustainability-oriented balanced scorecards—remains limited and often fragmented (25-27). The rapid diffusion of fintech, blockchain, and AI, together with the rise of ESG-driven credit ratings and climate transition risks, also means that traditional credit risk frameworks must be updated to reflect new sources of risk and interdependence (19, 23, 24).

In this context, there is a pressing need for an integrated, dynamic risk management model for the banking system that combines systems-thinking, multi-criteria evaluation, and advanced analytical techniques to capture credit, liquidity, operational, and sustainability risks in a unified framework. The aim of this study is to develop and analyze such a comprehensive risk management model for the banking system, with particular attention to credit risk, capital adequacy, and performance.

Methods and Materials

The statistical population of the present study consisted of 460 employees of Sepah Bank in the Qazvin region. In fact, all personnel of Sepah Bank, including staff in both frontline and headquarters units, comprised the study population. In this research, purposive sampling was used. More specifically, a particular type of purposive sampling known as expert sampling—designed for selecting knowledgeable and specialized individuals on a given topic—

was employed. From an operational perspective and regarding the data collection process, the necessary field investigations were conducted by attending the organization, examining the prevailing conditions and regulations, and assessing feasible data collection methods. Considering that the research was case-based, the study first examined the current procedures and prevailing conditions governing the identification of risk-generating indicators in the target organization, as well as the variables and indicators influencing this area, to achieve a general understanding of the organization's background in this regard. The data collection instruments included note-taking from previous studies and the fuzzy DEMATEL questionnaire. This questionnaire was used to gather expert opinions regarding the causal relationships among the five perspectives. The question posed in the questionnaire concerned the degree of direct influence between two perspectives, and the response scale ranged from "very weak" to "very strong."

To assess validity, standard questionnaires relevant to each method were utilized, and efforts were made to minimize ambiguity by using familiar expressions and defining terms and concepts to ensure consistent understanding among respondents, thereby ensuring content validity. To examine the reliability of the distributed questionnaire, two respondents were asked to answer the questionnaire twice within a two-week interval. After reviewing and analyzing the first and second responses, no significant or noticeable differences were observed. In total, 34 initial indicators were examined, and experts were asked to express their opinions regarding the degree of suitability of each indicator within the organization under study. The content validity of each indicator was subsequently assessed, and the resulting values were compared with the values in the Lawshe table (Mirzaei, 2011), indicating that all 25 indicators possessed the required content validity. Ultimately, 30 indicators were selected as the final set of indicators. The Lawshe coefficient table used in this study is presented in Table 1.

Table 1. Lawshe Coefficients Corresponding to the Number of Experts

Required Percentage for Validity	Number of Respondents
0.99	5
0.99	6
0.99	7
0.78	8
0.75	9
0.62	10
0.59	11
0.56	12
0.54	13
0.51	14
0.49	15
0.42	20
0.37	25
0.33	30
0.31	35
0.29	40

The individuals who completed the index selection and validation questionnaire were experts, mostly managers in various industries, who evaluated the indicators based on their knowledge and sufficient experience. Furthermore, the obtained expert opinions and the number of experts were considered, and the results were compared with Lawshe coefficients, which constitute an international standard. Based on these criteria, the indicators under examination were confirmed to possess the necessary content validity and, consequently, the required overall validity. Reliability in this research was calculated using Cronbach's alpha. If the alpha value was equal to or greater than 0.7, the reliability of the questionnaire was confirmed. Cronbach's alpha was calculated using SPSS software.

The information obtained from the experts was categorized so that, from among all indicators extracted from scientific articles, the indicators suitable for the present research could be selected. The experts' opinions regarding each alternative were then aggregated to obtain an integrated overall judgment. After collecting the required data, MATLAB and EXCEL software were employed at various stages to carry out the necessary computations. Additionally, SPSS software was used to examine the regression equation.

Findings and Results

Based on the reviewed literature, 30 indicators were extracted using the latest studies, as presented in Table 2. A review of previous literature shows that no research has been conducted in governmental organizations—including Sepah Bank—that evaluates performance with consideration of risk, incorporating both quantitative and qualitative indicators along with sustainability issues.

Table 2. Selected Indicators from the Research Literature for Performance Evaluation

Perspective	Indicators
Financial	Budget growth; level of cost adjustment; efforts to identify new revenue-generating sources (28); financial productivity; growth of urban revenues (5); cash flow volume; return on investment in capital projects (3).
Internal Processes	Labor productivity; existence of essential organizational standards (28); level of bureaucracy; interactions with other agencies (9); innovation in services; workforce efficiency (6); availability of low-cost service providers; explicit and transparent organizational objectives and mechanized performance evaluation systems (1).
Learning and Growth	Relevant training courses; salary levels compared with other organizations; employee educational attainment (29); human capital–information capital–emphasis on research and development (20); workforce familiarity with relevant policies and regulations (15).
Customer	Customer satisfaction; service quality (7); time spent by clients; quality of provided services (8); respect for clients; employee accountability (6); total quality management; client mental image (11).
Sustainability	Importance given to environmental green indicators; green suppliers; explicit and transparent goals toward greening management activities (23); cleaner work environment; in-service training on sustainability issues (24); return on investment in sustainability initiatives; innovation in green services; training courses related to environmental sustainability (17); green suppliers; environmentally friendly corporate image (18).

Since the selection of performance evaluation indicators for the units under study was conducted through face-to-face interviews and consultation with experts, those specialists possessing adequate technical knowledge and appropriate experience in this domain were chosen as interviewees. In this study, 20 experts were engaged, including 10 specialists from the regional headquarters with advanced academic qualifications and 10 branch managers from high-performing branches who had demonstrated positive performance outcomes. In other words, only individuals were selected who either worked at the regional headquarters in roles involving performance evaluation and risk control at Sepah Bank in the Qazvin Province, or were branch managers with exemplary performance in improving banking performance indicators.

According to the Lawshe table described in Chapter 3, since the number of experts is 24, the Lawshe coefficient must be at least 0.42. Additionally, after computing the content validity ratio (CVR) for the indicators under review, their CVR values are shown in Table 3. Each indicator with a CVR greater than or equal to 0.42 was accepted as a suitable indicator for evaluating the institutions under study; otherwise, the indicator was considered invalid.

Table 3. Validity of the Indicators Under Review

Criterion	Sub-criterion	C.V.R Value	Status
Financial Risk	Liquidity Risk	0.75	Acceptable
	Credit Risk	0.92	Acceptable

	Interest Rate Risk	0.75	Acceptable
	Exchange Rate Risk	0.75	Acceptable
	Legal Risk	0.92	Acceptable
	Market Risk	0.83	Acceptable
Customer-Orientation Risk	Inappropriate Staff Behavior with Customers	1.00	Acceptable
	Lack of Customer Satisfaction System (R-Code)	0.23	Rejected
	Rapid Change in Customer Preferences and Outdated Bank Products	1.00	Acceptable
	Failure to Fulfill Obligations and Customer Withdrawal from Bank Services	0.92	Acceptable
	Customer-Friendly Products of Competitor Banks	0.92	Acceptable
	Lack of Innovation in Services and Products	0.42	Acceptable
Internal Process Risk	Insufficient Use of Electronic Platforms	0.92	Acceptable
	Excessive Reliance on Unverified Methodologies	1.00	Acceptable
	Need for Rework	0.83	Acceptable
	Inadequate Access to Services	0.83	Acceptable
	Improper Understanding of Processes	0.67	Acceptable
	Delay in Task Completion	0.92	Acceptable
	Lack of Appropriate Equipment	0.34	Rejected
	Insufficient Coordination Between Units	1.00	Acceptable
Sustainability Risk	Excessive Use of Supplies (paper, cartridge, etc.)	0.92	Acceptable
	Excessive Use of Energy (water, electricity, gas, fuel)	0.92	Acceptable
	Emission of Banking Service Residuals	0.92	Acceptable
	Failure to Retrieve Documents	0.83	Acceptable
Learning and Growth Risk	Failure to Achieve Targeted Training Hours	0.67	Acceptable
	Failure to Provide Expert Instructors in the Banking System	0.75	Acceptable
	Lack of Alignment Between Course Content and Job Requirements	0.75	Acceptable
	Lack of Coordination Among Units in Conducting Courses	0.18	Rejected
	Inappropriate Timing of Training Courses	0.58	Acceptable
	Lack of Suitable Training Facilities and Equipment	0.58	Acceptable
	Lack of an Appropriate System for Evaluating Course Effectiveness	0.58	Acceptable
	Insufficient Attention to Innovation and Technology in Training	0.75	Acceptable
	Lack of Alignment Between Course Duration and Training Content	0.39	Rejected
	Outdated Training Content Failing to Meet Learner Needs	0.83	Acceptable

Furthermore, by examining the reliability of the questionnaire containing the indicators, it was found that the Cronbach's alpha calculated using SPSS was 0.99. Since a minimum of 0.70 is required for acceptable reliability, the reliability of the questionnaire was confirmed, as presented in Table 4.

Table 4. Reliability of the Questionnaire

Perspective	Cronbach's Alpha
Financial Risk	0.97
Customer-Orientation Risk	0.92
Internal Process Risk	0.95
Sustainability Risk	0.96
Learning and Growth Risk	0.97

After identifying the performance evaluation indicators, the next step involved identifying the causal relationships among the five perspectives of the Balanced Scorecard. To this end, expert opinions were obtained through a questionnaire designed to assess the degree of direct influence of indicators on one another. The response scale, based on a Likert-type system, ranged from "no influence" to "very high influence." The steps for analysis and evaluation are explained below.

Step 1: Aggregating Expert Opinions

After collecting expert responses, the opinions were aggregated. This was done by calculating the simple mean of responses from all participants (Table 5).

Table 5. Aggregated Expert Opinions Regarding the Intensity of Mutual Influence Among the Five Perspectives

Aggregated Mean of Expert Opinions	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	0.00 0.10 0.30	0.48 0.67 0.83	0.34 0.53 0.73	0.34 0.53 0.72	0.37 0.55 0.73
Customer-Orientation Risk	0.53 0.73 0.89	0.00 0.10 0.30	0.24 0.42 0.62	0.25 0.43 0.63	0.37 0.56 0.74
Internal Process Risk	0.40 0.60 0.77	0.35 0.53 0.71	0.00 0.10 0.30	0.40 0.60 0.79	0.32 0.51 0.70
Sustainability Risk	0.39 0.59 0.77	0.39 0.58 0.76	0.37 0.57 0.76	0.00 0.10 0.30	0.33 0.53 0.72
Learning and Growth Risk	0.47 0.67 0.84	0.36 0.55 0.75	0.67 0.52 0.71	0.31 0.50 0.69	0.00 0.10 0.30

Step 2: Defuzzification Using the CFCS Method

This method operates by determining the maximum and minimum boundaries of triangular fuzzy numbers and includes four steps.

Step 1: Normalizing the Decision Matrix

The fuzzy decision matrix was transformed as shown in Table 6.

Table 6. Normalized Matrix

New Triangular Values	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	0.00 0.11 0.34	0.54 0.76 0.94	0.39 0.60 0.82	0.39 0.60 0.81	0.42 0.62 0.82
Customer-Orientation Risk	0.60 0.82 1.00	0.00 0.11 0.34	0.27 0.48 0.70	0.28 0.49 0.71	0.42 0.63 0.84
Internal Process Risk	0.45 0.67 0.87	0.39 0.60 0.80	0.00 0.11 0.34	0.46 0.68 0.89	0.36 0.57 0.79
Sustainability Risk	0.44 0.66 0.86	0.44 0.65 0.86	0.42 0.64 0.85	0.00 0.11 0.34	0.37 0.59 0.81
Learning and Growth Risk	0.53 0.76 0.95	0.40 0.62 0.84	0.75 0.58 0.80	0.35 0.56 0.78	0.00 0.11 0.34

Step 2: Computing the Left and Right Normalized Values

The left (ls) and right (rs) normalized values for triangular fuzzy numbers were computed as shown in Table 7.

Table 7. Matrix of Left and Right Normalized Values

New Binary Values	Financial Risk (Xls/Xrs)	Customer-Orientation Risk (Xls/Xrs)	Internal Process Risk (Xls/Xrs)	Sustainability Risk (Xls/Xrs)	Learning and Growth Risk (Xls/Xrs)
Financial Risk	0.10 / 0.28	0.62 / 0.80	0.50 / 0.67	0.50 / 0.67	0.52 / 0.69
Customer-Orientation Risk	0.67 / 0.85	0.10 / 0.28	0.40 / 0.57	0.40 / 0.58	0.52 / 0.70
Internal Process Risk	0.55 / 0.73	0.50 / 0.67	0.10 / 0.28	0.56 / 0.74	0.47 / 0.65
Sustainability Risk	0.54 / 0.72	0.54 / 0.71	0.53 / 0.70	0.10 / 0.28	0.49 / 0.67
Learning and Growth Risk	0.62 / 0.80	0.51 / 0.69	0.70 / 0.66	0.47 / 0.64	0.10 / 0.28

Step 3: Calculating the Overall Normalized Crisp Values

Using Equation (1), the overall normalized crisp values have been calculated as shown in Table 8.

$$x_{ij}^{n} = \frac{xls_{ij}^{n}(1 - xls_{ij}^{n}) + xrs_{ij}^{n} \times xrs_{ij}^{n}}{1 - xls_{ij}^{n} + xrs_{ij}^{n}}$$

Table 8. Matrix of Overall Normalized Crisp Values

New Singleton Values	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	0.14	0.74	0.60	0.60	0.54
Customer-Orientation Risk	0.80	0.14	0.48	0.49	0.55
Internal Process Risk	0.66	0.60	0.14	0.67	0.50
Sustainability Risk	0.65	0.64	0.63	0.14	0.51
Learning and Growth Risk	0.74	0.62	0.67	0.56	0.13

Step 4: Calculating the Crisp Values

At this stage, the crisp values were obtained (Table 9).

Table 9. Matrix of Crisp Values

	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk	Sum
Financial Risk	0.13	0.66	0.53	0.53	0.48	2.32
Customer-Orientation Risk	0.71	0.13	0.43	0.43	0.48	2.18
Internal Process Risk	0.58	0.53	0.13	0.59	0.44	2.27
Sustainability Risk	0.58	0.57	0.56	0.13	0.46	2.29
Learning and Growth Risk	0.66	0.55	0.60	0.50	0.11	2.41
Sum	2.65	2.43	2.24	2.18	1.97	

Forming the Normalized Average Matrix

Next, the average matrix was normalized, as shown in Table 10.

Table 10. Normalized Average Matrix

Average Value Matrix	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	0.05	0.25	0.20	0.20	0.18
Customer-Orientation Risk	0.27	0.05	0.16	0.16	0.18
Internal Process Risk	0.22	0.20	0.05	0.22	0.17
Sustainability Risk	0.22	0.21	0.21	0.05	0.17
Learning and Growth Risk	0.25	0.21	0.22	0.19	0.04

Forming the Total Relation Matrix

In this step, the total relation matrix was obtained.

Table 11. Total Relation Matrix

Total Relation Matrix	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	-0.15	0.10	0.04	0.05	0.12
Customer-Orientation Risk	0.13	-0.13	0.00	0.00	0.05
Internal Process Risk	0.04	0.02	-0.15	0.06	0.09
Sustainability Risk	0.06	0.06	0.07	-0.13	0.00
Learning and Growth Risk	0.08	-0.03	0.04	0.03	-0.27

Calculating the Sum of Rows and Columns (ri and cj)

After forming the total relation matrix, the sum of the rows (ri) indicates the total influence that criterion i exerts on the other criteria, while the sum of the columns (cj) indicates the total influence that criterion j receives from the other criteria. These values are presented in Table 12.

Table 12. Calculation of ri and cj

	R	C
Financial Risk	0.16	0.16
Customer-Orientation Risk	0.05	0.09
Internal Process Risk	0.06	0.02
Sustainability Risk	0.06	0.01
Learning and Growth Risk	0.06	-0.01

Calculating ri + cj and ri − cj and the Weights of the Criteria

The values of ri + cj and ri − cj and the weights of the criteria are shown in Table 13.

Table 13. Calculation of ri + cj and ri − cj

	R + C	R − C	Perspective Weight
Financial Risk	0.22	-0.10	0.40
Customer-Orientation Risk	0.14	-0.05	0.25
Internal Process Risk	0.08	0.03	0.14
Sustainability Risk	0.07	0.05	0.12
Learning and Growth Risk	0.05	0.06	0.09

Plotting the Causal Relationship Diagram

The diagram shown in Figure 1 represents the causal relationships among the criteria, where the horizontal axis indicates ri + cj and the vertical axis indicates ri − cj. Criteria located above the horizontal axis represent causes, and those located below the horizontal axis represent effects. In this diagram, based on the values obtained in Table 13, a positive value of ri − cj indicates that factor i is a cause, whereas a negative value indicates that the factor is an effect. According to the plotted diagram, the financial, internal process, and learning and growth risk perspectives are causal, and the financial and customer perspectives are effects.

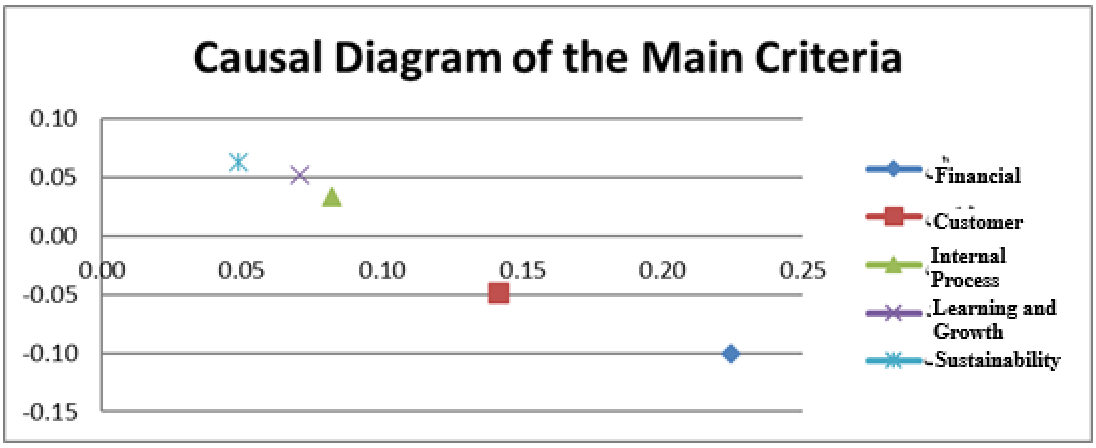

Figure 3. Causal Diagram of the Main Criteria

Step Eight: Calculating the Threshold Value p and Plotting the CRM Diagram

Each element in the total relation matrix indicates the extent to which factor i influences factor j. To determine the threshold value p for filtering out negligible causal effects, only those elements whose influence values in the total relation matrix are greater than the threshold (p) are displayed in the CRM diagram. The threshold p is defined as the mean of the elements in the total relation matrix. The average value of the total relation matrix for the main criteria was obtained as 0.011. Based on this threshold, the total relation matrix is transformed as shown in Table 14. Using the resulting matrix, the CRM diagram is drawn as in Figure 2.

Table 14. Total Relation Matrix Based on the Threshold Value

Threshold Matrix	Financial Risk	Customer-Orientation Risk	Internal Process Risk	Sustainability Risk	Learning and Growth Risk
Financial Risk	0.00	0.10	0.04	0.05	0.02
Customer-Orientation Risk	0.13	0.00	0.00	0.00	0.04
Internal Process Risk	0.04	0.02	0.00	0.06	0.09
Sustainability Risk	0.06	0.06	0.07	0.00	0.00
Learning and Growth Risk	0.08	0.04	0.06	0.03	0.00

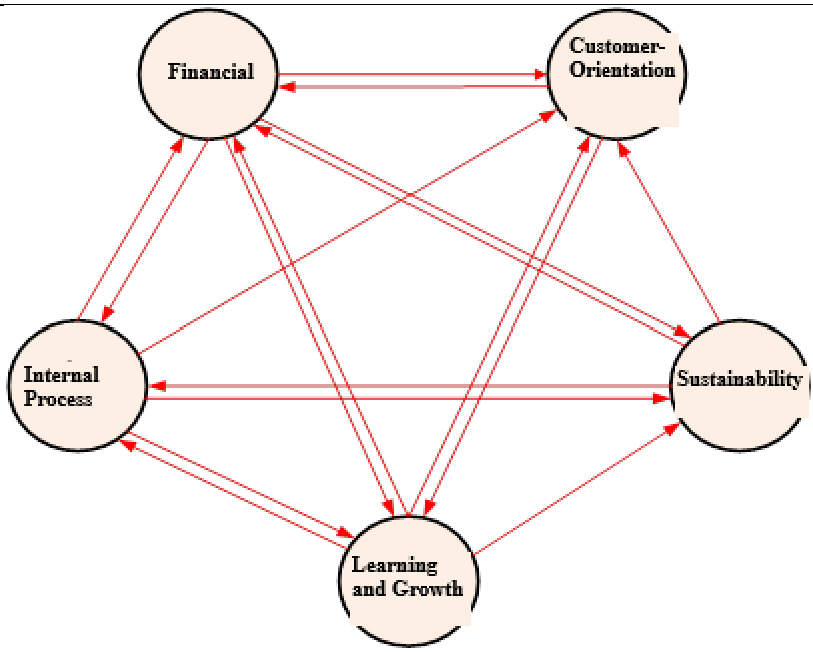

Figure 4. CRM Diagram

Discussion and Conclusion

The findings of the present study provide a comprehensive perspective on the dynamics of credit risk and its associated dimensions within the banking system, particularly through the integration of a sustainability-oriented balanced scorecard and multi-criteria decision-making approaches. The results indicate that among the five major perspectives—financial, customer, internal processes, sustainability, and learning and growth—significant causal relationships exist, with the learning and growth perspective exerting the strongest influence across other dimensions. This outcome aligns with the theoretical foundation that banks with strong human capital, ongoing training, and adaptive learning mechanisms are better equipped to identify, manage, and mitigate credit and operational risks (22). In addition, the results showed that sustainability risk emerged as one of the key causal factors influencing other performance indicators. This supports the view that environmental, social, and governance considerations are becoming integrated components of financial risk, especially as regulatory and environmental pressures reshape banks' lending criteria and credit evaluation systems (23, 24).

The strong influence of learning and growth risk highlights the increasing necessity for continuous staff development, updated credit assessment methodologies, and technological competence within banking institutions. This finding resonates with earlier research emphasizing the importance of human resource capabilities and training quality in strengthening credit risk management systems (29). Banks that invest steadily in human capital and provide staff with tools to evaluate borrower behavior, interpret risk models, and adapt to new fintech processes tend to achieve greater organizational resilience in the face of credit shocks (6). The empirical dominance of this perspective in the causal matrix suggests that credit risk is not merely a function of borrower characteristics or financial ratios, but also of the institution's internal competencies and preparedness, a result supported by the systems-thinking perspective of banking risk management (20).

Similarly, the financial risk perspective recorded a significant role as both a causal and effect factor in the system. The bidirectional influence observed in the results confirms that credit risk, liquidity risk, and market risk are interconnected in ways that generate feedback loops, consistent with the macro-financial interactions identified in multiyear modeling of bank credit, inflation, and default risks (2). The study's findings show that financial risk is shaped not only by external macroeconomic variables but also by internal decision-making structures and risk governance practices, echoing the conclusions of prior empirical studies on Iranian banks that highlighted the sensitivity of financial performance and capital adequacy to risk governance quality (11, 12). These results reinforce the notion that credit risk assessment must be embedded in broader financial stability frameworks in which capital buffers and risk-weighted assets form critical components of regulatory oversight (13).

Another central result involves the influential role of internal process risk. The analysis shows that weaknesses in operational procedures, outdated technologies, or excessive reliance on manual systems can intensify risk transmission across other dimensions. This finding is consistent with studies that emphasize the importance of operational efficiency and process integration in minimizing credit and market exposure (28). Internal inefficiencies, such as bottlenecks, manual errors, and misaligned processes, increase the probability of inaccurate credit assessment and weaken monitoring mechanisms, thereby increasing credit deterioration (8). Furthermore, research on risk-based supervision supports the view that internal processes form the core of an institution's risk posture, as operational vulnerabilities often translate into misclassification of risk, weak follow-up, and inaccurate provisioning practices (15).

The sustainability risk perspective, which emerged as a meaningful causal factor in the study, also deserves careful interpretation. The integration of environmental and resource-related inefficiencies into the risk evaluation system underscores the fact that sustainability considerations now influence a bank's long-term exposure and portfolio risk. This aligns with research on government-initiated environmental credit ratings, which shows that environmental performance directly affects credit risk exposure, particularly for institutions engaged in climate-sensitive lending (23). Additionally, studies have demonstrated that banks operating in environments with strong ESG frameworks benefit from lower default probabilities and better long-term risk management due to improved transparency and reduced regulatory penalties (24). The present findings therefore corroborate global evidence that sustainability factors should no longer be treated as peripheral considerations but core risk determinants, shaping borrower creditworthiness and bank portfolio composition.

Moreover, the results linking customer-orientation risk to broader performance outcomes reflect the increasingly strategic role of customer satisfaction, service quality, and relational stability in credit risk management. Empirical research in multiple contexts has shown that early warning signals of customer dissatisfaction—such as delayed payments, reduced usage of banking services, or repeated service complaints—can precede credit distress or loan defaults, reinforcing the essential interdependence between customer behavior and credit risk (6). In addition, customer-related risks are amplified in competitive markets, where banks with outdated products or weak customer communication strategies lose market share and absorb more credit-worthy borrowers' exit risks (16). The present study's results are consistent with these findings and underline the value of integrating customer analytics into risk monitoring frameworks.

The findings also support the emerging body of work on fintech and its influence on risk management. The study reveals that when banks adopt advanced analytical techniques and integrate fintech applications into their operations, they experience improvements in credit risk assessment accuracy and overall performance. This aligns with evidence showing that fintech enhances transparency, reduces information asymmetry, and strengthens real-time monitoring of borrower activity (17, 18). Furthermore, the potential of blockchain-based systems to reduce fraud, document manipulation, and collateral risks contributes to the reliability of credit evaluation processes (19). The results thus reinforce the argument that digital transformation and technological innovation should not be viewed as optional add-ons but essential risk-mitigation tools for contemporary banking systems.

In addition to these relationships, the study's application of a fuzzy multi-criteria approach and DEMATEL-based causal analysis supports the growing methodological recognition that credit risk is multidimensional and cannot be accurately captured through traditional single-variable indicators. Earlier work using grey MCDM in construction risk management demonstrated the value of integrating linguistic variables and expert judgment into risk modeling, especially in contexts characterized by uncertainty and incomplete data (25). Similarly, the use of fuzzy DEA to assess efficiency in uncertain environments shows that fuzzy logic enhances the robustness of performance evaluation under ambiguity (26). The present study extends these methodological innovations to the banking sector by combining sustainability-balanced scorecard perspectives with fuzzy causal modeling, thereby offering a more holistic and nuanced understanding of risk interactions (27).

Furthermore, the study's findings complement the literature on monetary policy and macro-financial determinants of credit risk. Research in Indonesia has shown that monetary tightening directly influences credit risk, especially in banks with high leverage and weak capital structures (3). Similarly, macroeconomic instability increases cost of capital, reduces borrower repayment capacity, and heightens default probabilities. These dynamics underscore the importance of integrating macroeconomic analysis into credit risk policy and strategic planning, a point reflected in the study's results indicating the strong influence of financial risk on other dimensions (2).

Taken together, the present findings illustrate that credit risk is not isolated but interacts with operational capabilities, sustainability factors, customer behavior, technological readiness, and macroeconomic forces. The study provides empirical confirmation of theoretical models that emphasize the systemic and multidimensional nature of risk (20). The causal relationships identified also offer banks an opportunity to prioritize interventions more effectively. For instance, improvements in learning and growth capabilities can indirectly enhance customer satisfaction, internal process quality, and environmental efficiency—ultimately reducing credit risk.

Despite its robust methodological design, the study has several limitations. The use of expert-based evaluations, although valuable for capturing tacit knowledge, may introduce subjective biases that cannot be fully controlled. The study's geographic focus on a specific banking region may also limit the generalizability of the findings to broader national or international banking environments. Additionally, while the fuzzy DEMATEL approach captures causal relationships, it cannot fully model dynamic changes in risk behavior over time, particularly in the presence of macroeconomic shocks or regulatory reforms. Finally, data limitations inherent to banking confidentiality may have restricted access to detailed borrower-level variables that could further enrich the analysis.

Future studies could incorporate longitudinal data to observe changes in risk interactions over time, especially during periods of economic instability. Researchers may also integrate machine-learning and artificial intelligence models with the balanced scorecard to explore advanced predictive capabilities. Expanding the scope of analysis to include multiple banks or cross-country comparisons would provide broader generalizability. Further work could also examine the moderating role of fintech adoption intensity, governance quality, or climate-related regulation on credit risk patterns.

Banks should prioritize strengthening their learning and growth systems, with a focus on continuous staff training and technological literacy. Operational process redesign should be implemented to reduce inefficiencies and enhance reliability. Sustainability should be embedded as a core component of risk evaluation rather than an auxiliary factor. Finally, integrating fintech tools—particularly blockchain and advanced analytics—into risk assessment frameworks can significantly improve accuracy and reduce overall credit risk exposure.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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