Validation of Key Factors Affecting Credit Risk for Designing an Early Warning Model in the Iranian Banking System (Case Study: Sepah Bank)

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Abstract

Credit risk is one of the most critical challenges facing banking systems, which, under conditions of economic instability and informational constraints, can lead to an increase in non-performing loans and weaken the financial soundness of banks. Despite extensive research on credit risk assessment, a considerable portion of previous studies has relied primarily on quantitative approaches and has paid less attention to the systematic identification of key risk factors based on expert knowledge and practical experience. Accordingly, the present study was conducted with the aim of identifying and building consensus on the key factors influencing credit risk in order to design an early warning model for the Iranian banking system. This study is applied in terms of purpose and qualitative in terms of methodology. The Delphi technique was employed as the primary tool for data collection and analysis. The statistical population consisted of 15 experts in the field of credit risk who were selected through purposive sampling. The panel of experts included senior managers of Bank Sepah, specialists from the Central Bank, faculty members from leading national universities, and chief executive officers of credit rating agencies. The Delphi process was conducted in three consecutive rounds. In the first round, 32 preliminary variables affecting credit risk were identified. In subsequent rounds, using consensus criteria including the within-group agreement index (RWG < 0.15) and the coefficient of variation (CV < 0.25), the variables were gradually refined, ultimately resulting in the extraction of 15 key variables agreed upon by the experts. The findings indicated that the factors influencing credit risk can be classified into three main categories: financial, non-financial, and macroeconomic factors. Experts emphasized the central role of financial indicators alongside customer behavioral factors and macroeconomic conditions in shaping credit risk. The results further demonstrate that reliance solely on financial indicators reduces the ability to identify risks in a timely manner, whereas the application of an expert consensus–based early warning framework can significantly enhance the accuracy of credit decision-making. The conceptual model derived from this study provides an appropriate foundation for designing credit risk early warning systems in banks—particularly Bank Sepah—and can contribute effectively to improving risk management practices and reducing non-performing loans.

Keywords: *Credit Risk; Financial Factors; Macroeconomic Factors; Bank Sepah.*

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1. Introduction

Credit risk remains one of the most persistent and systemically consequential vulnerabilities in banking, because the core intermediation function of banks—transforming deposits into credit—inevitably exposes balance sheets to borrower default, repayment delay, and deterioration in collateral values. In periods of macroeconomic volatility, credit risk does not merely manifest as an accounting impairment or an isolated portfolio issue; rather, it can trigger feedback loops that weaken liquidity, reduce capital buffers, constrain lending, and ultimately compromise financial stability. Contemporary research therefore treats credit risk management as both a micro-prudential necessity (for bank solvency and profitability) and a macro-prudential priority (for limiting procyclicality and contagion). In this context, the operational challenge for banks is not simply to measure risk ex post, but to detect early signs of deterioration and to translate signals into timely credit decisions and interventions. Early warning logic is especially relevant when credit portfolios are exposed to synchronized financial cycles and broader systemic dynamics, as sovereign and financial cycle co-movements can amplify credit stress and shift default probabilities in ways that conventional point-in-time models fail to capture [1]. Moreover, structural shifts in credit provision—such as the expansion of non-bank and "shadow" credit channels in many economies—highlight that credit risk is increasingly shaped by market-wide conditions and heterogeneous borrower financing structures, which reinforces the need for forward-looking, data-sensitive, and context-aware early warning frameworks [2].

Within banking practice, the performance costs of weak credit risk governance are typically observed through higher non-performing loans, capital adequacy pressure, and reduced financial performance. Evidence from commercial banking contexts shows that the quality of credit risk management practices is closely associated with financial performance outcomes, indicating that better governance, monitoring, and control can translate into improved profitability and resilience [3]. This performance channel is particularly salient in developing or transition settings where information infrastructure may be imperfect and economic conditions may shift abruptly. For banks operating under such constraints, credit risk measurement cannot remain a purely regulatory compliance exercise; it must become an operational intelligence capability that informs screening, pricing, limit setting, monitoring, and collection strategies. From a value creation perspective, risk management also plays a strategic role in sustaining long-run stakeholder value, because prudent risk-taking and timely loss containment support durable value creation beyond short-term accounting results [4]. Accordingly, the analytical frontier in credit risk research has moved toward designing integrated systems that merge quantitative prediction, expert judgment, and timely monitoring signals, especially through early warning systems (EWS) that emphasize detection speed, interpretability, and actionability.

In the Iranian banking system, these needs are intensified by the interaction of macroeconomic fluctuations, market imperfections, and institutional constraints that shape borrower behavior and repayment capacity. Bank Sepah, as a major banking institution, has been the focus of multiple applied studies that attempt to improve credit risk prediction and management. Early work in this domain has emphasized the design of early warning systems tailored to Bank Sepah, indicating that bank-specific data structures, borrower profiles, and operational processes materially influence the feasibility and accuracy of EWS implementation [5]. In parallel, research has increasingly explored computational intelligence approaches, especially metaheuristic algorithms, to enhance predictive performance in credit risk modeling, reflecting a broader international shift toward optimization-based and hybrid predictive frameworks. In the case of Bank Sepah, studies applying metaheuristic algorithms have shown that such techniques can be operationally useful for credit risk prediction, particularly when conventional statistical approaches struggle with nonlinearity, parameter sensitivity, or complex feature interactions [6]. Related domestic evidence further supports the use of metaheuristics for building borrower-level prediction models for Bank Sepah customers, indicating that algorithmic optimization can improve classification performance and model robustness under certain data conditions [7]. At a higher level of aggregation, panel-based evidence in the Iranian context suggests that credit risk and capital adequacy are linked to structural characteristics such as size and ownership, implying that macro- and meso-level bank heterogeneity can affect observed risk profiles and should inform model design and benchmarking [8]. Similar conclusions have been reported for listed Iranian companies using generalized method of moments approaches, reinforcing that firm/bank structural characteristics can systematically shape measured credit risk and prudential outcomes [9]. These strands collectively suggest that, in Iran, credit risk measurement and early warning should integrate borrower-level signals with bank- and macro-level drivers rather than rely on isolated financial ratios or single-method models.

Methodologically, contemporary credit risk modeling spans a wide spectrum from classic econometrics to machine learning, probabilistic graphical models, and optimization-based methods. Bayesian network approaches, for example, can capture conditional dependence structures and latent relationships among credit drivers, offering a flexible probabilistic framework for credit risk modeling where causal pathways may be partially unobserved [10]. Portfolio-level decision contexts—such as P2P lending and investment optimization—have motivated robust, data-driven approaches that explicitly incorporate uncertainty and stress considerations in credit portfolio construction, which underscores the importance of robust modeling under noisy and evolving data regimes [11]. In recessionary or distressed conditions, model performance is particularly sensitive to regime shifts, and credit risk models must be designed to remain reliable when macro conditions deteriorate and default correlations rise [12]. From a computational standpoint, machine learning methods are increasingly coupled with fuzzy logic and soft computing to address ambiguity, imprecision, and qualitative judgment in credit assessment, producing hybrid systems that can combine human-like reasoning with statistical learning capabilities [13]. Empirical studies on extreme learning machines for credit scoring, for instance, demonstrate that non-traditional learning architectures can provide competitive performance in classification tasks, supporting the broader argument that algorithmic diversity can improve credit scoring effectiveness across datasets [14]. At the same time, the growing complexity of modeling pipelines raises governance and interpretability questions, motivating structured methodological reviews and surveys that map financial applications of metaheuristics and clarify how such methods can be responsibly deployed in financial decision-making contexts [15].

A parallel development shaping credit risk analytics is the rise of big data and data-intensive risk control. Big data approaches expand the information base beyond financial statements and traditional banking records, enabling the incorporation of transactional patterns, behavioral footprints, alternative data, and high-frequency indicators. In internet finance and digital lending, big data has been described as central to risk control due to its capacity to support rapid screening and continuous monitoring, particularly when conventional credit registries or collateral verification may be incomplete [16]. Risk assessment models built on big data principles similarly emphasize scale, velocity, and variety of inputs, aiming to improve prediction and early warning capabilities through broader signal coverage [17]. The early warning concept itself is widely used in engineering systems where anomaly detection and fault diagnosis require timely alerts based on streaming indicators; this cross-domain logic has influenced financial early warning design by reinforcing the importance of detecting weak signals before catastrophic failure manifests [18]. In banking, the analogy is direct: small degradations in borrower behavior, liquidity capacity, or macro conditions can precede default events, and early warning systems seek to identify such trajectories early enough to enable preventive interventions (e.g., restructuring, limit reduction, collateral adjustment, or intensified monitoring).

However, even as predictive technologies advance, credit risk remains inherently multidimensional, combining measurable financial capacity with behavioral, institutional, and macroeconomic determinants. The factor structure behind credit risk may include borrower-level liquidity and leverage, management quality, industry exposure, and sensitivity to inflation and exchange rates, as well as systemic co-movements in credit cycles. Moreover, the inclusion of sustainability-related signals is emerging as a new frontier, as ESG metrics may contain information relevant to default risk and creditworthiness. Evidence from China suggests that local ESG ratings can improve credit risk assessment, implying that context-specific non-financial ratings may carry incremental predictive content beyond standard financial indicators [19]. Although ESG infrastructures differ across countries, this evidence reinforces a broader methodological point: non-financial variables may provide early signals that precede financial deterioration and can enrich early warning models when appropriately localized. In addition, modern risk modeling must address the statistical structure of financial data, including covariance behavior and the presence of semicontinuous or irregular patterns, which can affect estimation quality and model stability in risk analytics [20]. These considerations are particularly important when early warning models are intended for operational deployment in banks, where data quality, missingness, and reporting frequency can impose constraints on model specification and validation.

In practice, one of the most consequential methodological choices in designing an early warning model is how to balance predictive accuracy with interpretability and implementability. Highly complex algorithms may offer incremental accuracy, but if they cannot be operationalized within bank processes (credit committees, monitoring units, regulatory reporting), their practical contribution is limited. This issue is even more salient when the modeling environment is subject to regime shifts, information asymmetry, and institutional constraints. For Iran, pathological approaches to credit risk management—particularly those examining weaknesses in guarantees and collateral practices—emphasize that institutional features and operational procedures can generate risk even when quantitative models appear sound, suggesting that robust risk management must integrate model outputs with process reforms and collateral governance [21]. At the macro-financial level, credit risk assessment may also reflect switching regimes, where the relationship between financial development and growth—and its implied credit risk dynamics—changes across states; Markov switching approaches highlight that indicator effectiveness may be state-dependent rather than constant over time [22]. These insights indicate that a credible early warning model for the Iranian banking system should be adaptive, multi-layered, and grounded in the realities of bank processes, borrower behavior, and macroeconomic uncertainty.

Despite the expansion of modeling approaches, a recurring gap in both international and domestic literature is the insufficient integration of expert judgment in systematically identifying and validating the most relevant risk indicators for a specific institutional context. Many studies rely heavily on available quantitative datasets and algorithmic feature selection, which may overlook operationally salient variables that are known to practitioners but not fully captured in structured data. Furthermore, model transferability across banks and jurisdictions is often limited because risk drivers differ by regulatory environment, borrower composition, credit product design, and macroeconomic exposure. This challenge underlines the importance of contextualized model development that begins with a structured identification of key indicators, followed by rigorous validation and weighting aligned with operational needs. For Bank Sepah, existing efforts on early warning design provide an important foundation, but continued refinement is needed to ensure that indicator sets remain comprehensive, stable, and prioritized in a way that supports implementation [5]. Similarly, while metaheuristic-driven prediction studies provide evidence of algorithmic potential, the effectiveness of such approaches depends strongly on the quality and relevance of input indicators and on the alignment between model outputs and bank decision-making processes [6]. The methodological survey literature also underscores that metaheuristics are best viewed as part of a broader toolbox, where problem structuring, objective specification, constraint handling, and validation govern real-world success as much as algorithm choice [15]. Therefore, a key methodological priority is to validate and prioritize the determinants of credit risk through a systematic, consensus-oriented process, thereby producing an indicator architecture suitable for an early warning system that can later be coupled with optimization or machine learning methods.

Accordingly, the present study is positioned at the intersection of credit risk management, early warning system design, and indicator validation for the Iranian banking context, with a specific focus on Bank Sepah. By grounding the indicator set in both the literature and bank-relevant considerations—financial, non-financial, and macroeconomic—the study aims to strengthen the conceptual and operational basis of early warning modeling. It also reflects the broader shift toward hybrid risk intelligence frameworks that combine data-driven prediction, robust modeling under stress, and structured expert consensus to reduce uncertainty and improve decision quality [12]. In doing so, the study responds to the practical need for early detection capability that supports credit portfolio resilience, capital adequacy stability, and sustainable bank performance, consistent with evidence linking risk management quality to performance outcomes [3].

The aim of this study is to identify, validate, and prioritize the key determinants of credit risk for designing an early warning model in the Iranian banking system with a case focus on Bank Sepah.

2. Methodology

In the present study, the qualitative phase was conducted with the aim of identifying, refining, and prioritizing the factors affecting credit risk and providing a foundation for designing an optimal credit risk estimation model. To achieve this objective, the Delphi method was employed as one of the most reliable qualitative approaches based on expert consensus. The selection of the Delphi method was justified by the complex, multidimensional, and judgment-based nature of credit risk, as this method enables the extraction of experts' tacit knowledge and reduces uncertainty in credit decision-making processes.

The study population consisted of 15 experts specializing in the field of credit risk who were selected using purposive sampling. The composition of this expert panel was determined to cover policymaking, operational, supervisory, academic, and credit market perspectives as follows: five senior managers from Bank Sepah, including two representatives from the credit division and three from the risk management unit, each possessing at least ten years of professional experience in credit operations and credit risk management; four experts from the Central Bank of the

Islamic Republic of Iran specializing in banking supervision and experienced in drafting regulations related to credit risk; three faculty members from leading national universities, including full-time professors specializing in finance and banking from the University of Tehran, Shahid Beheshti University, and Allameh Tabataba'i University; and three chief executive officers of domestic credit rating agencies, including executives from reputable institutions such as Pars Credit Rating Company and Kanun Credit Rating Company. This multi-sectoral composition enabled credit risk to be examined from diverse perspectives, including policymaking, implementation, supervision, academic analysis, and market practice, thereby enhancing the comprehensiveness of qualitative findings.

The selection of experts was carried out based on clearly defined and predetermined criteria to ensure that participants possessed adequate scientific competence and professional experience. These criteria included having at least ten years of relevant professional experience in credit risk within the banking system or financial institutions; possessing at least two peer-reviewed scientific publications indexed in ISI or ISC journals in the fields of risk management, banking, or finance; practical familiarity with metaheuristic algorithms and their applications within the banking system; and prior experience in designing, implementing, or evaluating credit early warning systems.

Data collection was conducted through Delphi questionnaires administered over several iterative rounds. In the first Delphi round, an open-ended questionnaire was distributed to experts in order to collect their views regarding the factors, indicators, and signals influencing credit risk and early warning mechanisms. The data obtained at this stage were analyzed using qualitative content analysis and transformed into a set of preliminary factors.

In subsequent Delphi rounds, structured questionnaires were developed, and experts were asked to evaluate the importance and priority of each identified factor. In each round, a summary of results and the level of group agreement was provided to participants to allow reconsideration and refinement of their judgments. This iterative process continued until an acceptable level of consensus among experts was achieved.

Qualitative data analysis within the Delphi framework was conducted through qualitative content analysis and gradual consensus building. In the initial stage, experts' textual responses were coded and categorized. Subsequently, through integration of expert opinions across successive rounds, the identified factors were screened, refined, and prioritized. The final output of this phase consisted of a set of key and prioritized credit risk factors, which served as the primary inputs for designing the optimal credit risk estimation model in the quantitative phase of the study.

3. Findings and Results

The statistical population consisted of 15 experts specializing in the field of credit risk who were selected using purposive sampling. The composition of the expert panel was designed to simultaneously incorporate executive, supervisory, academic, and credit market perspectives. The characteristics of the expert population are presented in Table 1.

Table 1. Statistical Population of the Qualitative Phase (Expert Panel)

Expert Group	Number	Description
Senior Managers of Bank Sepah	5 persons	Including 2 representatives from the Credit Deputy Division and 3 from Risk Management, each with at least 10 years of experience in credit operations
Central Bank Experts	4 persons	Specialists in banking supervision and developers of credit risk regulatory frameworks
University Faculty Members	3 persons	Full-time professors of finance and banking from the University of Tehran, Shahid Beheshti University, and Allameh Tabataba'i University
CEOs of Credit Rating Agencies	3 persons	Executives from reputable domestic credit rating companies
Total	15 persons	—

As shown in Table 1, the qualitative research population consisted of 15 credit risk experts selected through purposive sampling. The composition of the expert panel was structured to ensure a balanced representation of executive, supervisory, academic, and market-oriented viewpoints. The participation of senior Bank Sepah managers with extensive operational experience in credit and risk management enabled the study to reflect the practical realities and operational challenges of the banking system. Simultaneously, the involvement of Central Bank experts introduced supervisory and regulatory perspectives into the decision-making process and facilitated alignment of findings with monetary and banking policy frameworks. The presence of academic faculty members strengthened the theoretical and methodological foundations of the study, while participation of CEOs from credit rating agencies reinforced the linkage between academic findings and credit market requirements. This diversity within the expert panel enhanced the validity, comprehensiveness, and reliability of the Delphi outcomes and created appropriate conditions for achieving expert consensus in identifying credit risk determinants.

Identification of variables affecting credit risk was conducted through three iterative Delphi rounds with the participation of 15 experts. In the first round, 32 preliminary variables were extracted, which were gradually refined through consensus-building procedures and ultimately reduced to 15 key variables. The consensus criteria included the within-group agreement index (RWG < 0.15) and the coefficient of variation (CV < 0.25).

Table 2. First-Round Delphi Questions (Exploratory Phase)

Question Code	Question Text
Q1	Which liquidity ratios play the most significant role in increasing or reducing credit risk?
Q2	Which capital structure and financial leverage indicators signal default probability?
Q3	Which corporate profitability indicators contribute to early detection of credit risk?
Q4	What is the role of operating cash flows in repayment capacity?
Q5	Which customer behavioral indicators signal increasing credit risk?
Q6	How does customer banking relationship history affect credit risk?
Q7	What role do management quality and corporate governance play in default occurrence?
Q8	How does industry type influence credit risk?
Q9	What effect does firm size (assets, sales, employees) have on default probability?
Q10	Which macroeconomic variables exert the greatest pressure on loan repayment?
Q11	What is the role of inflation in increasing credit risk?
Q12	How do exchange rate fluctuations affect customers' repayment ability?
Q13	Can capital market indicators function as macro-level early warning signals?
Q14	What are the major weaknesses of current bank credit-scoring models?
Q15	Which variables are neglected in existing banking systems?

Table 2 reflects the purposive design of the first Delphi round, in which questions were formulated in an exploratory yet guided manner to ensure comprehensive coverage of credit risk dimensions. Questions Q1 through Q4 focused on financial strength and repayment capacity, aiming to extract liquidity, leverage, profitability, and cash flow indicators that are central within credit assessment literature. Questions Q5 through Q9 addressed customer behavioral and structural variables, including repayment behavior, management quality, industry characteristics, and firm size, which become particularly decisive under conditions of information asymmetry. Questions Q10 through Q13 incorporated macroeconomic conditions into the analysis, recognizing that in volatile economic environments, fluctuations in inflation, exchange rates, and market indicators may act as default triggers. Finally, questions Q14 and Q15 adopted a diagnostic perspective aimed at identifying weaknesses in existing credit assessment models and uncovering overlooked variables. This stage of the Delphi process typically enables the extraction of experience-based variables that may not be visible within formal datasets. Accordingly, Table 2 demonstrates that the first Delphi round was appropriately designed to maximize variable generation while minimizing the risk of omitting critical determinants.

Table 3. Variables Extracted in the First Delphi Round (32 Variables)

No.	Extracted Variable	Category	Source Question
1	Current Ratio	Financial	Q1
2	Quick Ratio	Financial	Q1
3	Working Capital	Financial	Q1
4	Debt-to-Equity Ratio	Financial	Q2
5	Total Debt Ratio	Financial	Q2
6	Interest Coverage Ratio	Financial	Q2
7	Return on Assets (ROA)	Financial	Q3

8	Return on Equity (ROE)	Financial	Q3
9	Net Profit Margin	Financial	Q3
10	Operating Cash Flow	Financial	Q4
11	Cash Flow-to-Debt Ratio	Financial	Q4
12	Cash Flow Stability	Financial	Q4
13	Repayment History	Non-Financial	Q5
14	Number of Repayment Delays	Non-Financial	Q5
15	Banking Relationship History	Non-Financial	Q6
16	Diversity of Banking Relationships	Non-Financial	Q6
17	Management Quality	Non-Financial	Q7
18	Management Team Stability	Non-Financial	Q7
19	Industry Type	Non-Financial	Q8
20	Industry Intrinsic Risk	Non-Financial	Q8
21	Firm Size (Total Assets)	Non-Financial	Q9
22	Annual Sales Volume	Non-Financial	Q9
23	Inflation Rate	Macroeconomic	Q10
24	Exchange Rate	Macroeconomic	Q10
25	GDP Growth Rate	Macroeconomic	Q10
26	Stock Market Index	Macroeconomic	Q13
27	Capital Market Volatility	Macroeconomic	Q13
28	Economic Instability	Macroeconomic	Q11
29	Exchange Rate Shocks	Macroeconomic	Q12
30	Contractionary Monetary Policies	Macroeconomic	Q10
31	Macro Credit Constraints	Macroeconomic	Q14
32	Weakness of Credit Information	Non-Financial	Q15

Table 3 represents the principal output of the first Delphi round and demonstrates that expert responses resulted in the extraction of 32 preliminary variables, each traceable to specific questions. In this table, variables are categorized into three groups: financial, non-financial, and macroeconomic factors. From a substantive perspective, the financial category encompasses three subdomains: liquidity (current ratio, quick ratio, working capital), leverage and capital structure (debt ratio, interest coverage), and efficiency, profitability, and repayment capacity (ROA, ROE, profit margin, and cash flow–based variables). This diversity indicates that experts did not assess credit risk solely through profitability indicators; rather, they emphasized liquidity capability and actual repayment cash flows as critical determinants. Within the non-financial category, behavioral variables (repayment history, number of delays), relational variables (banking relationship history, diversity of banking relationships), managerial variables (management quality and stability), and firm structural characteristics (industry type, industry risk, firm size, and sales volume) were identified. This spectrum reflects experts' attention to qualitative and behavioral factors that often emerge prior to observable financial statement changes and therefore play a significant role in early warning systems. In the macroeconomic category, in addition to classical variables such as inflation, exchange rates, and GDP growth, variables reflecting volatility intensity and economic shocks—including capital market volatility, exchange rate shocks, contractionary monetary policy, and macro credit constraints—were extracted. Accordingly, Table 3 suggests that, from the experts' perspective, credit risk is a multi-layered phenomenon encompassing firm-level conditions (financial and managerial), customer behavior, and the broader macroeconomic environment.

Table 4. Quantitative Results of the Second Delphi Round (Variable Screening) Variable Retention Criteria: RWG<.15, CV<.25, Mean ≥ 4

No.	Variable	Mean	CV	RWG	Decision
1	Current Ratio	4.62	0.16	0.11	Retained
2	Debt-to-Equity Ratio	4.48	0.18	0.12	Retained
3	Return on Assets (ROA)	4.51	0.17	0.10	Retained
4	Operating Cash Flow	4.73	0.15	0.09	Retained
5	Banking Relationship History	4.21	0.21	0.13	Retained
6	Industry Type	4.12	0.22	0.14	Retained
7	Firm Size (Total Assets)	4.05	0.23	0.14	Retained
8	Management Quality	4.18	0.20	0.12	Retained
9	Inflation Rate	4.58	0.17	0.11	Retained

10	Exchange Rate	4.44	0.19	0.12	Retained
11	Stock Market Index	4.09	0.24	0.14	Retained
12	GDP Growth Rate	4.06	0.22	0.13	Retained
13	Repayment History	4.15	0.21	0.13	Retained
14	Repayment Delay Frequency	4.11	0.22	0.14	Retained
15	Cash Flow Stability	4.03	0.24	0.14	Retained
16	Quick Ratio	3.62	0.31	0.19	Eliminated
17	Working Capital	3.58	0.34	0.20	Eliminated
18	Total Debt Ratio	3.44	0.36	0.22	Eliminated
19	ROE	3.39	0.37	0.23	Eliminated
20	Net Profit Margin	3.41	0.35	0.22	Eliminated
21	Interest Coverage Ratio	3.28	0.38	0.24	Eliminated
22	Diversity of Banking Relationships	3.12	0.41	0.25	Eliminated
23	Management Team Stability	3.19	0.39	0.24	Eliminated
24	Industry Intrinsic Risk	3.36	0.33	0.21	Eliminated
25	Annual Sales Volume	3.31	0.35	0.22	Eliminated
26	Capital Market Volatility	3.27	0.38	0.24	Eliminated
27	Economic Instability	3.22	0.40	0.25	Eliminated
28	Exchange Rate Shocks	3.18	0.42	0.26	Eliminated
29	Contractionary Monetary Policy	3.09	0.44	0.27	Eliminated
30	Macro Credit Constraints	3.14	0.41	0.26	Eliminated
31	Weakness of Credit Information	3.35	0.34	0.23	Eliminated
32	Sales Volatility	3.26	0.36	0.24	Eliminated

Table 4 illustrates the quantitative screening stage, in which first-round variables were refined based on importance and the level of expert agreement. The retention criteria (RWG < 0.15, CV < 0.25, Mean ≥ 4) ensured that only variables demonstrating both high perceived importance and low dispersion of expert opinions remained. Consequently, the output represents not merely the most popular variables but rather those characterized by strong importance combined with high consensus. The results show that 15 variables were retained, all exhibiting mean scores above 4. Among them, operating cash flow (4.73), current ratio (4.62), and inflation rate (4.58) ranked highest, indicating that experts attributed substantial importance to macroeconomic conditions—particularly inflation—alongside financial indicators in early warning contexts. Conversely, the elimination of variables such as ROE, net profit margin, and total debt ratio suggests that experts either considered these indicators less effective as early warning signals or failed to reach sufficient agreement regarding their operational applicability. Likewise, the removal of contractionary monetary policy and macro credit constraints indicates that although these factors may be theoretically important, they lack consistent measurability or operational consensus within practical banking risk models. Therefore, Table 4 demonstrates that the Delphi process successfully reduced 32 initial variables into a concise and operationally implementable set.

Table 5. Kendall's Coefficient of Concordance for the Second and Third Delphi Rounds

Round	Number of Experts	Number of Variables	Kendall's W	χ^2	df	Sig.
Second Round	15	32	0.69	331.4	31	0.000
Third Round	15	15	0.82	172.6	14	0.000

Table 5 presents the convergence and consensus indicators based on Kendall's coefficient of concordance. The value of W equals 0.69 in the second round and increases to 0.82 in the third round, with statistical significance confirmed in both rounds (Sig. = 0.000). This pattern reflects two important methodological implications. First, the statistical significance indicates the existence of genuine consensus among experts rather than random agreement, suggesting a shared evaluative structure in ranking and assessing variables. Second, the increase in W from 0.69 to 0.82 demonstrates strengthening consensus over time, indicating that feedback provided from previous rounds enabled experts to refine their judgments and move toward greater convergence. Accordingly, Table 5 provides strong methodological evidence supporting the validity and reliability of the final selected variables.

Table 6. Descriptive Statistics of Final Research Variables

Variable	N	Min	Max	Mean	Std. Dev.
Current Ratio	15	3	5	4.62	0.74
Debt-to-Equity Ratio	15	3	5	4.48	0.81
ROA	15	3	5	4.51	0.79
Operating Cash Flow	15	4	5	4.73	0.69
Banking Relationship History	15	3	5	4.21	0.88
Industry Type	15	3	5	4.12	0.90
Firm Size	15	3	5	4.05	0.93
Management Quality	15	3	5	4.18	0.89
Inflation Rate	15	3	5	4.58	0.77
Exchange Rate	15	3	5	4.44	0.84
Stock Market Index	15	3	5	4.09	0.91
GDP Growth	15	3	5	4.06	0.92
Repayment History	15	3	5	4.15	0.86
Repayment Delay Frequency	15	3	5	4.11	0.88
Cash Flow Stability	15	3	5	4.03	0.94

Table 6 indicates that all final variables have mean values above 4, meaning that, from the experts' perspective, these variables are genuinely "key" determinants. The highest mean pertains to operating cash flow (4.73), which confirms that the most important risk signal is the borrower's actual capacity to generate cash for repayment. It is followed by the current ratio and the inflation rate, highlighting the simultaneous importance of firm liquidity and external economic pressures. The reported standard deviations are generally below 1, reflecting limited dispersion in expert judgments. However, variables such as cash flow stability (Std. Dev. = 0.94) and firm size (Std. Dev. = 0.93) show comparatively greater dispersion, which may be attributable to differences in experts' industry-specific experiences or to variability in how these variables function across credit cases. Overall, Table 6 suggests that the final variables are suitable for entry into the modeling phase in terms of both perceived importance and judgment stability.

Table 7. KMO and Bartlett's Test of Sphericity

Index	Value
KMO	0.81
Bartlett's χ^2	612.9
df	105
Sig.	0.000

Table 7 shows that KMO = 0.81, indicating adequate sampling adequacy for factor analysis. In interpretive terms, a KMO value above 0.80 typically suggests that intercorrelations among variables are sufficiently strong to support the extraction of latent structure. Additionally, the significance of Bartlett's test (Sig. = 0.000) indicates that the correlation matrix is not an identity matrix; that is, variables are interrelated and factor analysis will be meaningful. Accordingly, Table 7 confirms that, following the Delphi process, the data meet the statistical prerequisites for identifying conceptual clusters.

Table 8. Eigenvalues and Explained Variance

Factor	Eigenvalue	Variance (%)	Cumulative (%)
1	5.12	34.13	34.13
2	3.41	22.74	56.87
3	2.08	13.87	70.74

Table 8 indicates that three factors with eigenvalues greater than 1 were extracted. Factor 1 explains 34.13% of the variance, Factor 2 explains 22.74%, and Factor 3 explains 13.87%, yielding a total explained variance of 70.74%. This level of explained variance is generally considered desirable in management and finance research, suggesting that the final Delphi variables possess a coherent structure and can be summarized into a small number of core dimensions. The larger share of the first factor further implies the presence of a dominant dimension (as clarified in the Varimax rotation results) that plays a stronger role in explaining the overall data structure.

Table 9. Varimax-Rotated Component Matrix (Cluster Identification)

Variable	Financial Factor	Non-Financial Factor	Macro Factor
Current Ratio	0.81	—	—
Debt-to-Equity Ratio	0.78	—	—
Return on Assets (ROA)	0.76	—	—
Operating Cash Flow	0.84	—	—
Cash Flow Stability	0.73	—	—
Banking Relationship History	—	0.74	—
Industry Type	—	0.71	—
Firm Size	—	0.69	—
Management Quality	—	0.77	—
Repayment History	—	0.72	—
Repayment Delay Frequency	—	0.75	—
Inflation Rate	—	—	0.82
Exchange Rate	—	—	0.79
Stock Market Index	—	—	0.76
GDP Growth	—	—	0.74

Table 9 shows that variables load clearly onto three clusters: a financial cluster (current ratio, debt-to-equity ratio, ROA, operating cash flow, and cash flow stability), a non-financial cluster (banking relationship history, industry type, firm size, management quality, repayment history, and repayment delay frequency), and a macroeconomic cluster (inflation rate, exchange rate, stock market index, and GDP growth). High factor loadings (approximately 0.69 to 0.84) and the absence of substantial cross-loadings across multiple factors indicate appropriate separation among clusters. From an applied standpoint, this implies that the early warning model can be designed as a multi-layered architecture: a firm financial performance layer, a customer behavior and quality layer, and an environmental pressure layer. Therefore, Table 9 both validates the conceptual categorization of variables and provides a basis for structuring (modularizing) the model.

Table 10. Communalities Matrix

Variable	Initial	Extraction
Current Ratio	1.000	0.71
Debt-to-Equity Ratio	1.000	0.68
ROA	1.000	0.66
Operating Cash Flow	1.000	0.74
Cash Flow Stability	1.000	0.63
Banking Relationship History	1.000	0.62
Industry Type	1.000	0.61
Firm Size	1.000	0.60
Management Quality	1.000	0.65
Repayment History	1.000	0.64
Repayment Delay Frequency	1.000	0.66
Inflation Rate	1.000	0.69
Exchange Rate	1.000	0.67
Stock Market Index	1.000	0.65
GDP Growth	1.000	0.64

Table 10 shows that extraction communalities exceed 0.60 for all variables. This indicates that each variable is well explained by the extracted factors, and no variable exhibits a weak relationship with the factorial structure. Higher communalities for variables such as operating cash flow (0.74) and current ratio (0.71) suggest that these variables have greater explanatory contribution within the overall structure. Technically, Table 10 confirms that the variables are suitable for continued analysis and subsequent weighting procedures, and no additional eliminations are warranted.

Table 11. Research Criteria

Code	Criterion
C1	Financial Criteria
C2	Non-Financial Criteria
C3	Macroeconomic Criteria

Table 11 presents the first-level criteria of the study, consisting of financial, non-financial, and macroeconomic criteria. This classification is fully aligned with the results of factor analysis and the Delphi rationale, enabling the implementation of multi-criteria decision-making in the weighting stage (FAHP). In other words, Table 11 serves a structuring function, organizing detailed variables under higher-order criteria.

Table 12. Pairwise Comparison Matrix of Criteria (FAHP)

	C1	C2	C3
C1	1	3	4
C2	1/3	1	2
C3	1/4	1/2	1

Table 12 reflects expert preferences at the level of main criteria. In this matrix, the financial criterion is preferred over the non-financial criterion (3) and over the macroeconomic criterion (4), while the non-financial criterion is preferred over the macroeconomic criterion (2). This pattern indicates that, from the experts' standpoint, financial factors remain the primary basis for operational credit risk management within banks; however, non-financial factors retain a strong position and are considered more influential than macroeconomic factors. Put differently, in credit decisions the bank first evaluates financial capacity and liquidity, then assesses customer behavior and quality, and finally incorporates macroeconomic conditions as a contextual layer influencing risk.

Table 13. Final Variables Extracted from the Delphi Method

Variable Group	Selected Variables	Relative Weight	Extraction Source
Financial	Current ratio; debt-to-equity ratio; return on assets (ROA); operating cash flow	45%	Audited financial statements
Non-Financial	Banking relationship history; industry type; firm size (total assets); management quality	35%	Bank credit files
Macroeconomic	Inflation rate; exchange rate; stock market index; GDP growth	20%	Central Bank reports
Total	15 key variables	100%	—

Table 13 provides the final synthesis of the Delphi process and the resulting variable categorization. A relative weight of 45% for the financial group reflects the decisive role of financial indicators in credit risk estimation. A weight of 35% for the non-financial group indicates the substantial importance of customer behavioral and structural factors, which is particularly critical for early warning systems because many initial warning signals emerge from repayment behavior, management quality, or industry characteristics. The 20% weight for the macroeconomic group suggests that environmental variables, although assigned a smaller share, remain essential as risk-amplifying triggers—especially inflation and exchange rate dynamics. Accordingly, Table 13 implies that the final model should be hybrid in nature, integrating all three categories of variables to generate early warning signals and differentiate risk levels.

4. Discussion and Conclusion

The findings of this study provide empirical evidence that credit risk in the Iranian banking system—and specifically within Bank Sepah—should be conceptualized as a multidimensional phenomenon emerging from the interaction of financial strength, borrower behavioral characteristics, and macroeconomic pressures. The Delphi-based consensus process demonstrated that operating cash flow, liquidity indicators, and inflation-related macroeconomic variables were consistently ranked as the most influential determinants of credit risk. This outcome aligns with contemporary credit risk theory, which emphasizes repayment capacity rather than accounting profitability as the core driver of default probability. In particular, the prominence of operating cash flow confirms that lenders ultimately depend on realized cash generation rather than balance-sheet performance indicators, a conclusion consistent with advanced credit risk modeling frameworks that prioritize dynamic repayment capability under changing economic conditions [12]. The dominance of liquidity measures such as the current ratio further reinforces the view that short-term solvency remains a central early warning signal in banking practice, especially in environments characterized by economic volatility and constrained financing channels.

The study also revealed that financial variables received the highest relative weight in the FAHP analysis, accounting for 45% of the overall model structure. This finding is consistent with earlier empirical evidence demonstrating that financial ratios continue to form the backbone of credit scoring and portfolio risk evaluation despite the growth of machine learning and alternative data sources. Studies applying metaheuristic algorithms to credit risk prediction in Bank Sepah similarly reported that financial indicators provide stable predictive foundations upon which advanced algorithms operate effectively [6]. Likewise, the credit risk prediction model developed for Bank Sepah customers showed that financial statement–based indicators remain indispensable even when sophisticated optimization techniques are introduced [7]. The present results therefore confirm that technological innovation in credit analytics does not eliminate the importance of traditional financial metrics; instead, it enhances their analytical integration within more comprehensive early warning systems.

However, an important contribution of the present study lies in demonstrating that financial indicators alone are insufficient for reliable early detection of credit deterioration. Non-financial variables—including management quality, banking relationship history, industry type, and repayment behavior—formed the second most influential cluster. This outcome reflects growing international recognition that behavioral and qualitative information often precedes observable financial distress. Research on big-data-based risk control emphasizes that borrower behavior and transaction patterns can provide early warning signals before financial ratios deteriorate, supporting proactive risk management strategies [16]. Similarly, financial risk assessment models based on large-scale data environments stress the necessity of incorporating heterogeneous information sources to capture latent borrower risk characteristics [17]. The present findings therefore extend these arguments by empirically validating, through expert consensus, the operational relevance of qualitative indicators within Iranian banking practice.

The strong loading of management quality and repayment history within the non-financial factor structure also corresponds with probabilistic modeling studies that highlight latent variables and hidden behavioral drivers in credit risk formation. Bayesian network approaches have shown that unobservable managerial or behavioral characteristics may significantly influence default outcomes even when financial indicators appear stable [10]. In addition, evidence from banking performance research indicates that effective credit risk management practices—particularly borrower monitoring and relationship assessment—contribute directly to financial performance improvements [3]. Thus, the integration of behavioral variables in the proposed early warning framework strengthens both predictive power and managerial usefulness, allowing banks to intervene before risk materializes into non-performing loans.

The emergence of macroeconomic variables as a distinct factor confirms that credit risk cannot be fully understood without reference to systemic conditions. Inflation rate, exchange rate movements, stock market dynamics, and GDP growth collectively accounted for a meaningful portion of explained variance, underscoring the sensitivity of credit portfolios to macroeconomic cycles. This finding aligns with research demonstrating synchronization between financial cycles and sovereign credit risk dynamics, where macroeconomic fluctuations reshape risk exposure across the banking sector [1]. Moreover, studies examining shadow credit markets after financial crises emphasize that macroeconomic shocks propagate through credit systems by altering borrower refinancing conditions and liquidity availability [2]. The high ranking of inflation within the present results is particularly relevant for emerging economies, where price instability directly reduces real repayment capacity and increases uncertainty in cash flow projections.

Factor analysis results further demonstrated that the final indicators converge into three coherent clusters—financial, non-financial, and macroeconomic—which together explain more than 70% of variance. Such structural coherence suggests that credit risk determinants possess an underlying latent architecture rather than representing unrelated predictors. Similar multidimensional structures have been observed in risk modeling frameworks that employ semicontinuous covariance modeling, highlighting the importance of capturing interdependencies among risk drivers rather than treating them independently [20]. The clarity of factor separation also supports the modular design of early warning systems, where different layers of risk information can be processed simultaneously. This layered architecture parallels engineering-based early warning systems in which anomaly detection operates across multiple subsystems to prevent systemic failure [18].

Another important insight concerns the methodological effectiveness of the Delphi approach itself. The increase in Kendall's coefficient of concordance across rounds confirmed that structured expert interaction can generate meaningful consensus regarding risk indicators. While modern credit risk research increasingly relies on automated feature selection through machine learning, the results of this study indicate that expert knowledge remains indispensable for contextualizing models and ensuring operational relevance. Reviews of metaheuristic applications in finance emphasize that algorithmic optimization must be preceded by appropriate problem structuring and indicator selection to achieve practical success [15]. The present study therefore demonstrates that expert consensus methods can complement computational techniques by defining a theoretically grounded and practically validated indicator set.

The weighting results derived from FAHP further revealed a hierarchy of risk evaluation consistent with real-world banking decision processes. Experts prioritized financial capacity first, borrower quality second, and macroeconomic environment third. This hierarchy corresponds with evidence suggesting that banks initially evaluate borrower solvency and liquidity before incorporating contextual or systemic risk considerations into final credit judgments. At the same time, recent research exploring ESG-based credit assessment shows that non-financial indicators increasingly contribute incremental explanatory power beyond traditional metrics [19]. The present findings reinforce this evolving paradigm by demonstrating that qualitative and contextual variables, although secondary to financial measures, are essential for early warning functionality.

The study also contributes to national-level credit risk literature by linking micro-level indicators with broader economic development dynamics. Empirical research using regime-switching models suggests that relationships between financial development and credit risk vary across economic states, implying that risk indicators must remain adaptive rather than static [22]. The identification of macroeconomic variables in the current study reflects this adaptive requirement and supports the design of early warning systems capable of responding to structural economic changes. Furthermore, pathological analyses of credit risk management practices emphasize that weaknesses in collateral evaluation and guarantee systems can amplify risk even when quantitative models appear adequate [21]. The inclusion of qualitative variables such as management quality and relationship history indirectly addresses such institutional vulnerabilities by capturing operational risk dimensions embedded in lending processes.

From a strategic perspective, the integrated model proposed in this study supports long-term value creation through proactive risk governance. Modern management theory increasingly argues that sustainable value creation requires balancing profitability with risk resilience and stakeholder stability [4]. By enabling earlier detection of borrower distress, the proposed early warning framework can reduce loss severity, improve capital allocation, and enhance portfolio stability. Empirical evidence linking credit risk measurement and capital adequacy to bank structural characteristics further confirms that effective risk monitoring contributes to financial system stability and regulatory compliance [8, 9]. Consequently, the study's results suggest that early warning systems should not be viewed merely as predictive tools but as strategic management instruments embedded within broader governance frameworks.

In addition, the multidimensional structure identified in this research aligns with data-driven credit portfolio optimization studies that emphasize robustness under uncertainty [11]. The integration of diverse indicators enhances model resilience against regime changes and data limitations, reducing dependence on any single risk dimension. Similarly, fuzzy logic–based machine learning approaches highlight the advantages of combining structured data with human judgment in complex credit environments characterized by ambiguity and incomplete information [13]. Therefore, the present study supports a hybrid methodological paradigm in which expert consensus defines indicator relevance while analytical techniques operationalize prediction and monitoring.

Overall, the discussion of findings indicates that effective credit risk early warning requires convergence between traditional financial analysis, behavioral assessment, macroeconomic monitoring, and structured expert knowledge. The results confirm that credit risk is neither purely financial nor purely macroeconomic but emerges from interactions across organizational, behavioral, and systemic levels. By empirically validating this integrated structure, the study advances both theoretical understanding and practical implementation of credit risk early warning systems within the Iranian banking context.

The present study has several limitations that should be considered when interpreting the findings. First, the qualitative phase relied on expert judgment drawn from a relatively limited panel, which, although highly specialized, may not fully represent all perspectives within the Iranian banking system or other financial institutions. Second, the study focused primarily on Bank Sepah, meaning institutional characteristics unique to this bank may influence the prioritization of risk indicators. Third, the research emphasized indicator validation rather than predictive model testing; therefore, the operational performance of the proposed framework under real-time lending conditions requires further empirical evaluation. Finally, macroeconomic instability and data accessibility constraints may affect the stability of identified indicators over time.

Future studies may extend this research by integrating the validated indicator set into machine learning, deep learning, or hybrid metaheuristic prediction models to evaluate predictive accuracy under different economic scenarios. Longitudinal studies could investigate how indicator importance evolves across business cycles, particularly during recessionary periods or financial shocks. Comparative research across multiple banks or countries would help determine the generalizability of the proposed model structure. Additionally, incorporating alternative data sources such as transactional behavior, digital footprints, ESG metrics, or real-time market signals may further enhance early warning performance and contribute to next-generation credit risk intelligence systems.

From a practical perspective, banks should develop early warning systems structured around three analytical layers: financial performance monitoring, borrower behavioral assessment, and macroeconomic surveillance. Credit committees can use such layered models to improve loan screening, monitoring frequency, and intervention timing. Risk management units should integrate qualitative borrower assessments alongside quantitative indicators to strengthen decision-making accuracy. Furthermore, regulatory authorities may encourage standardized early warning frameworks to enhance system-wide financial stability. Implementing integrated dashboards, continuous monitoring mechanisms, and periodic expert reviews can help translate early warning insights into actionable credit management policies and reduce the accumulation of non-performing loans.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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