Design and Validation of a Financial Distress Risk Assessment Model Based on Interpretive Structural Modeling

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Abstract: This study examines the hierarchical structure of risks influencing the financial distress of banks using the Interpretive Structural Modeling (ISM) method. Financial distress, regarded as the stage preceding bankruptcy, arises from the complex interaction of internal and external factors affecting banks and has far-reaching implications for financial stability and economic growth. In this regard, key risk components—including liquidity risk, credit risk, market risk, and operational risk—were first identified, and their interrelationships were analyzed using ISM. The research findings revealed that the ratio of net profit to total bank assets and the ratio of net working capital to total bank assets, with impact coefficients of 99% and 94%, respectively, play the most significant roles in reducing the financial distress risk of listed banks. Furthermore, market risk, the market-to-book value ratio, and the total debt-to-total assets ratio, each with an impact coefficient of 91%, showed a similar effect in mitigating this risk. Other variables, such as operational risk, interest rate risk, net profit to equity, and total asset size, also demonstrated approximately 80% influence and ranked in subsequent positions. The power–dependence analysis showed that liquidity risk, with 100% driving power and 17% dependence, is positioned in the independent zone, whereas credit risk and operational risk, characterized by high driving power and medium dependence, are situated in the linkage zone. Variables such as net profit, working capital, and market risk, with 100% dependence but low driving power, are placed in the dependent zone.

Keywords: Financial distress, Interpretive Structural Modeling (ISM), liquidity risk

1. Introduction

The stability and resilience of the banking system play a pivotal role in safeguarding national financial security and sustaining macroeconomic growth. Banks act as critical intermediaries by channeling funds between savers and borrowers, facilitating payment systems, and enabling capital formation; however, their exposure to various types of risks, if not properly managed, can lead to severe financial distress and even systemic crises [1]. Financial distress occurs when a bank's operational and financial performance deteriorates to the extent that it struggles to meet its obligations, representing a stage that may precede bankruptcy [2]. Understanding and mitigating the drivers of financial distress is therefore essential not only for bank managers and regulators but also for maintaining investor confidence and preserving economic stability [3].

Recent studies emphasize that the mechanisms triggering bank distress are multifaceted and interrelated, encompassing both internal and external factors [4]. Internal determinants often include weak asset quality, insufficient capital buffers, liquidity mismatches, and operational inefficiencies [5]. External contributors stem from macroeconomic instability, such as fluctuating oil prices, exchange rate volatility, and shocks in global financial markets [6]. In an increasingly interconnected global economy, shocks in one segment of the financial system can propagate quickly, amplifying risk exposures across banks and other institutions [1]. This has led to heightened interest in robust risk assessment frameworks that can model the complex interactions between risk categories rather than evaluating them in isolation [3, 7].

Financial distress modeling has evolved considerably over recent decades, moving beyond simple ratio-based approaches toward integrated and dynamic frameworks. Traditional indicators such as the ratio of net profit to total assets or net working capital to total assets remain useful but can be insufficient for anticipating cascading effects under stress [4]. Methods like the KMV model and Value at Risk (VaR) have been widely applied to capture credit and market risk exposures [7]. However, their limitations in explaining interdependencies among risk drivers have motivated researchers to adopt more interpretive and structural approaches [8]. Interpretive Structural Modeling (ISM), in particular, provides a means to systematically identify, classify, and map the hierarchical relationships among risk factors, offering decision-makers a visual and analytical understanding of how one risk can trigger or intensify another [9, 10].

In emerging markets such as Iran, the banking sector faces unique structural vulnerabilities due to rapid financial liberalization, exposure to global oil price cycles, and evolving regulatory frameworks [11]. Studies show that credit risk remains a dominant driver of distress in Iranian banks, influenced by poor loan portfolio quality and insufficient credit risk management strategies [12, 13]. Liquidity risk has also emerged as a critical vulnerability, especially under conditions of macroeconomic instability and capital flight [14, 15]. The interplay between liquidity shortages and credit deterioration creates feedback loops that amplify vulnerability and reduce resilience [16, 17]. Moreover, the adoption of new financial technologies (fintech) and digital platforms, while beneficial for efficiency, has introduced additional operational and cyber risks that may heighten exposure if not effectively governed [14, 15].

Systemic risk remains a critical concern because the failure of one or more banks can spill over into the broader financial network, affecting asset pricing, interbank markets, and economic growth [18, 19]. Research on systemic stress indexes and contagion effects demonstrates that early detection of distress signals within banks is vital for preventing shock amplification [1, 20]. Central banks and regulators increasingly rely on integrated indicators to anticipate and contain crises; however, most existing risk frameworks still lack interpretive depth and fail to capture contextual realities in developing economies [21, 22]. For example, findings on asset and liability management models show the importance of aligning internal financial structures with dynamic risk environments to support stability [21].

Contemporary scholarship highlights that financial distress is not merely a result of single risk exposures but an emergent property of interconnected and layered risk networks [3]. For instance, earnings forecast inaccuracy has been associated with increased vulnerability to distress, particularly where governance mechanisms are weak and transparency is limited [10]. At the same time, corporate governance practices—such as board independence, risk oversight, and regulatory compliance—can mitigate the likelihood of distress and systemic disruption [23, 24]. Studies also show that adopting sustainability-oriented and green banking practices can strengthen customer trust and long-term financial resilience, indirectly contributing to distress mitigation [24].

Another dimension is the macroeconomic environment in which banks operate. Oil price fluctuations, for example, exert a direct influence on the liquidity and capital adequacy of energy-dependent economies' banks [6]. When combined with geopolitical shocks and economic sanctions, such volatility further undermines capital adequacy and loan performance [11, 25]. Moreover, the digital transformation of banking introduces opportunities for efficiency but also heightens complexity and operational risk [14, 15]. Hence, modern frameworks must address multi-layered risk interdependencies while remaining sensitive to contextual and regulatory nuances [12, 13].

To respond to these challenges, interpretive and system-oriented modeling approaches such as ISM have gained traction in risk research and practice. ISM allows experts to collectively map out the cause-and-effect structure among risk elements, producing a hierarchical view that clarifies which risks act as fundamental drivers and which are largely dependent [8, 9]. Such insights can inform targeted risk mitigation strategies, capital planning, and governance reforms [10, 25]. For example, if liquidity risk is found to have the highest driving power, regulators can prioritize liquidity buffers and stress testing frameworks [16, 17]. Likewise, if credit risk appears as a second-layer driver, improving credit appraisal systems and provisioning standards becomes critical [12, 13].

Cross-national evidence underscores the relevance of such integrative frameworks. Research in the European Union highlights the role of macroprudential policies in enhancing resilience and mitigating systemic vulnerability [18]. In Indonesia and other dual banking systems, competition and regulatory quality have been shown to influence systemic risk transmission [19]. Tanzanian studies reveal that the quality of credit risk management practices directly affects the financial performance and stability of commercial banks [22]. These findings affirm that while risk structures are context-dependent, the need for dynamic, interconnected modeling is universal.

In Iran's context, where economic volatility and international restrictions create additional layers of uncertainty, there is an urgent need for localized and adaptable risk assessment models. Prior research points to the limitations of conventional ratio analysis and foreign frameworks in capturing domestic complexities [4, 26]. Integrating interpretive expert-driven models with robust data analytics can bridge this gap, enabling banks and regulators to identify root causes, anticipate stress propagation, and implement proactive interventions [9, 10]. Moreover, combining qualitative expert consensus with quantitative risk metrics strengthens the validity and operational relevance of risk models [8, 11].

Building upon these insights, the present study aims to design and validate a comprehensive financial distress risk assessment model tailored to the banking sector by leveraging Interpretive Structural Modeling.

2. Methodology

This study is applied in nature and was conducted using a qualitative approach. Its objective was to design and validate a model for measuring the financial distress risk of banks by employing the Interpretive Structural Modeling (ISM) method. In the first stage, by reviewing the theoretical foundations and previous studies, a set of key indicators influencing banks' financial distress—including liquidity risk, market risk, credit risk, operational risk, the ratio of net working capital to total assets, and the ratio of net profit to total bank assets—were identified. These indicators were used as the primary criteria for developing the conceptual model of the research. Then, using the ISM method, the relationships among these variables were analyzed and their hierarchical structure was extracted to provide a coherent framework for assessing financial distress risk.

In the validation phase of the research instrument, feedback was obtained from academic experts in accounting, financial management, banking, and financial engineering, as well as specialists working at the Central Bank. The qualitative data were collected through interviews with 23 of these experts during the summer of 2024. The validity of the measurement tool was refined and finalized based on scientific documentation, banking standards, and specialized feedback. This process ensured that the designed model was not only theoretically grounded but also operationally aligned with the realities of the banking industry, confirming its practical applicability for measuring banks' financial distress risk.

3. Findings and Results

According to the results presented in Table 1, the study population consisted of 23 experts in the fields of finance and banking who met the required professional and experiential qualifications to participate in the study. These individuals possessed four key attributes: relevant knowledge and experience, willingness to collaborate, sufficient time to participate, and effective communication skills. Based on the collected data, 78% of participants had more than 10 years of work experience, reflecting their deep familiarity with banking and financial issues. Additionally, 61% of the participants were employed at the Central Bank, while 39% were university faculty members, providing a balanced combination of academic and practical perspectives. In terms of gender, 70% were male and 30% were female. Regarding age distribution, the highest frequency belonged to the 31–49 age group (61%). This demographic composition demonstrates that the study sample had the necessary expertise, experience, and diversity of viewpoints to validate the proposed research model.

Table 1. Research Demographics

Type of Characteristic	Characteristic	Number	Relative Frequency (%)
Related Work Experience	3–5 years	3	13%
	6–10 years	2	9%
	More than 10 years	18	78%
Gender	Male	16	70%
	Female	7	30%
Age	Under 30 years	3	13%
	31–49 years	14	61%
	Over 50 years	6	26%
Employment Status	Employed at Central Bank	14	61%
	University Faculty	9	39%

The ISM approach can categorize and prioritize the elements used to measure financial distress risk by applying the Structural Self-Interaction Matrix (SSIM) technique for associated concepts. In other words, this matrix analyzes the relationships among the elements and uses the following four symbols to indicate the type of relationship between element *i* and element *j*: a one-way relationship from row *i* to column *j* (V); a one-way relationship from column *j* to row *i* (A); a bidirectional and correlated relationship between *i* and *j* (X); and no relationship between *i* and *j* (O).

Table 2. Structural Self-Interaction Matrix of Associated Concepts (Raw Data of Main Indicators)

Structural Modeling Access Matrix	Net Working Capital to Total Assets	Net Profit to Total Assets	Bank Liquidity Risk	Bank Market Risk	Bank Credit Risk	Bank Operational Risk
Net Working Capital to Total Assets	1	9X, 5V, 5O, 4A	22A, 1X	16X, 2O, 4A, 1V	19A, 2X, 2V	17A, 1V, 3O, 2X
Net Profit to Total Assets	-	1	21A, 2X	11X, 5A, 1O, 6V	6X, 17A	5X, 17A, 1V
Bank Liquidity Risk	-	-	1	21V, 2X	9X, 11V, 1A, 2O	21V, 1A, 1O
Bank Market Risk	-	-	-	1	14X, 1V, 6A, 2O	4X, 8V, 11A

Bank Credit Risk	-	-	-	-	1	20V, 1X, 2A
Bank Operational Risk	-	-	-	-	-	1

Table 3. Structural Self-Interaction Matrix of Associated Concepts (Processed Data of Main Indicators)

Structural Modeling Access Matrix	Net Working Capital to Total Assets	Net Profit to Total Assets	Bank Liquidity Risk	Bank Market Risk	Bank Credit Risk	Bank Operational Risk
Net Working Capital to Total Assets	1	X	A	X	A	A
Net Profit to Total Assets	-	1	A	X	A	A
Bank Liquidity Risk	-	-	1	V	V	V
Bank Market Risk	-	-	-	1	X	A
Bank Credit Risk	-	-	-	-	1	V
Bank Operational Risk	-	-	-	-	-	1

Based on the analysis of the SSIM in Tables 2 and 3, it was determined that there was a high level of consensus among the experts regarding the relationship between the indicators “net working capital to total assets” and “bank liquidity risk,” as 22 out of the 23 experts selected the option A, meaning that bank liquidity risk leads to net working capital to total assets. Furthermore, bank liquidity risk was also found to lead to bank market risk and bank operational risk because 21 out of the 23 experts selected the option A. On the other hand, expert opinions diverged slightly regarding the relationship between “net working capital to total assets” and “net profit to total assets”: 9 out of the 23 experts chose X (bidirectional relationship), 5 selected V (net working capital to total assets influences net profit to total assets), 4 selected A (net profit to total assets influences net working capital to total assets), and 5 selected O (no relationship).

Subsequently, based on the relationships between the concepts of the financial distress risk reduction model for listed banks derived from the Structural Self-Interaction Matrix (SSIM), the Initial Reachability Matrix (IRM) of associated concepts was constructed. This matrix displays driving power with a value of 1 (X and V) and driving power with a value of 0 (A and O).

Table 4. Initial Reachability Matrix (IRM) of Associated Concepts (Raw Data of Main Indicators)

Reachability Matrix in Interpretive Structural Modeling	Net Working Capital to Total Assets	Net Profit to Total Assets	Bank Liquidity Risk	Bank Market Risk	Bank Credit Risk	Bank Operational Risk
Net Working Capital to Total Assets	1	X	A	X	A	A
Net Profit to Total Assets	X	1	A	X	A	A
Bank Liquidity Risk	V	V	1	V	V	V
Bank Market Risk	X	X	A	1	X	A
Bank Credit Risk	V	V	A	X	1	V
Bank Operational Risk	V	V	A	V	A	1

Table 5. Processed Reachability Matrix (IRM) of Associated Concepts (Main Indicators)

Reachability Matrix in Interpretive Structural Modeling	Net Working Capital to Total Assets	Net Profit to Total Assets	Bank Liquidity Risk	Bank Market Risk	Bank Credit Risk	Bank Operational Risk	Absolute Driving Power (IRM)	Relative Driving Power (IRM)
Net Working Capital to Total Assets	1	1	0	1	0	0	3	50%
Net Profit to Total Assets	1	1	0	1	0	0	3	50%
Bank Liquidity Risk	1	1	1	1	1	1	6	100%

Bank Market Risk	1	1	0	1	1	0	4	67%
Bank Credit Risk	1	1	0	1	1	1	5	83%
Bank Operational Risk	1	1	0	1	0	1	4	67%
Absolute Dependence (IRM)	6	6	1	6	3	3	–	
Relative Dependence (IRM)	100%	100%	17%	100%	50%	50%	–	

Based on Tables 4 and 5, the calculations of the Reachability Matrix in the Interpretive Structural Modeling (ISM) show that bank liquidity risk has the highest driving power because its relative driving power is calculated at 100% (6 out of 6). In fact, the driving power of bank credit risk is 83% (5 out of 6), while the driving power of bank market risk and bank operational risk is 67% (4 out of 6). On the other hand, net working capital to total assets and net profit to total assets both show 50% (3 out of 6). Moreover, the relative dependence for net working capital to total assets, bank market risk, and net profit to total assets was measured at exactly 100% (6 out of 6), while for bank credit risk and bank operational risk, it was measured at 50% (3 out of 6).

Next, the consistency of the Reachability Matrix, based on the frequency percentages in ISM, was examined using the MicMac matrix. According to the consistency of the Reachability Matrix, the highest agreement among experts' responses was observed for bank liquidity risk at 100%, followed by bank credit risk at 83%, bank market risk and bank operational risk at 67%, and net working capital to total assets and net profit to total assets at 50% (3 out of 6).

In the ISM model, the levels of the criteria for reducing financial distress risk in listed banks were drawn based on the prioritization obtained from top to bottom.

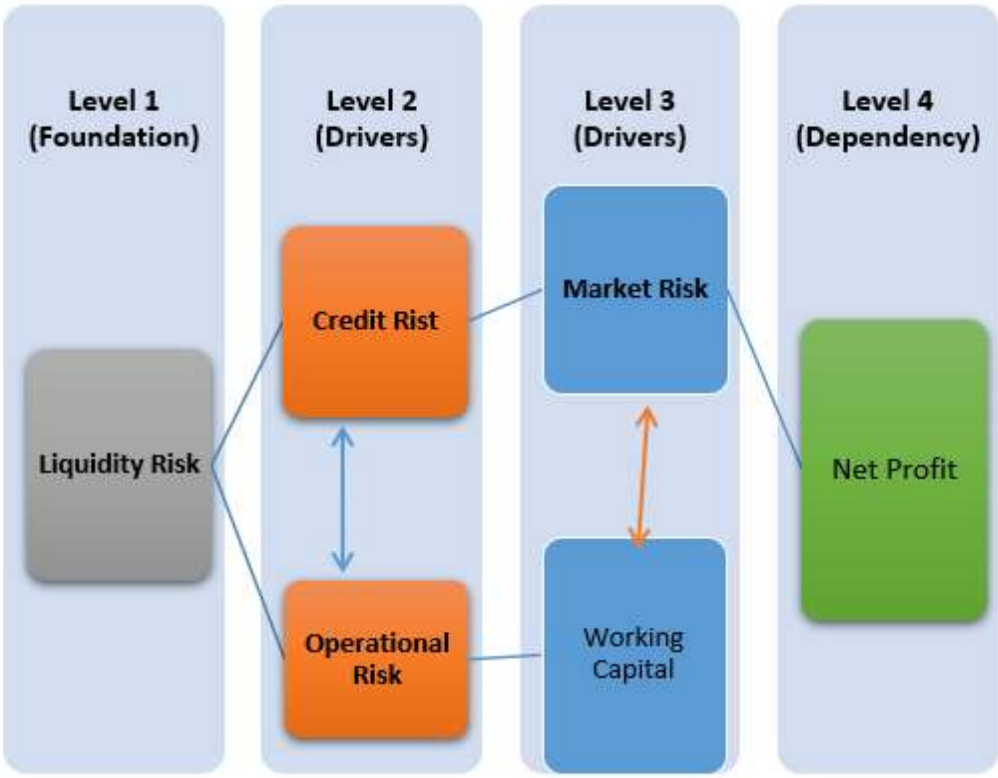

Figure 1. ISM Model for Determining the Levels and Priorities of Criteria

In Figure 1, the analysis of the direct driving and dependence map of the six factors is presented. The ISM model is constructed based on the levels obtained in the previous step and the scenario of the final Reachability Matrix within the Central Bank. At the top level, "bank liquidity risk" appears first; then, at the second level, "bank credit risk" and "bank operational risk" show high dependence on bank liquidity risk. From another perspective, at the lowest level (fourth level), "bank market risk" is directly influenced by "net working capital to total assets" and "net profit to total assets." In fact, in the second level of the ISM model, "bank credit risk" and "bank operational risk" have equal priority, while at the third level, "net working capital to total assets" and "net profit to total assets" hold similar priority.

After determining the relationships and levels of the criteria, they can be illustrated as an interpretive structural model using the MicMac matrix. Accordingly, based on the Reachability Matrix in ISM, the driving power–dependence diagram of the associated concepts is presented in Figure 2.

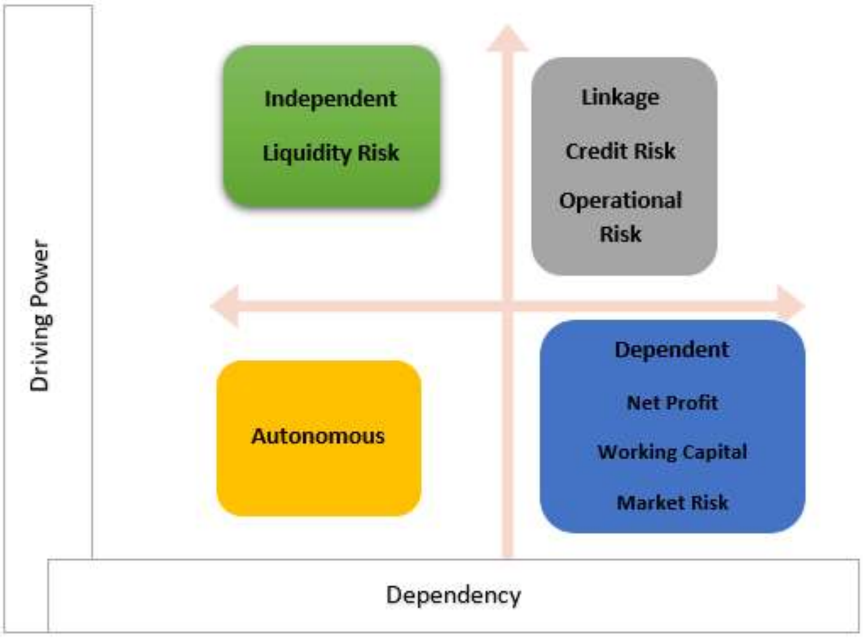

Figure 2. Driving Power–Dependence in Interpretive Structural Modeling

According to the study's findings, the driving power–dependence diagram shows that bank liquidity risk has the highest driving power at 100% and the lowest dependence at 17%, placing it in the independent quadrant (low dependence and high driving power). In contrast, bank credit risk and bank operational risk exhibit high driving power—83% and 67%, respectively—and medium dependence at 50%, placing them in the linkage quadrant (high driving power and medium dependence). Meanwhile, net working capital to total assets, net profit to total assets, and bank market risk have the highest dependence at 100% and the lowest driving power at 50%, positioning them in the dependent quadrant. Notably, based on the relationships between the concepts in the Structural Self-Interaction Matrix, no criteria were located in the autonomous quadrant (disconnected and low driving power).

4. Discussion and Conclusion

The present study aimed to design and validate an interpretive structural model (ISM) to assess and map the interrelationships among risk factors influencing financial distress in banks. The results revealed a clear hierarchical structure in which bank liquidity risk emerged as the most dominant driver, demonstrating the highest relative driving power (100%) and the lowest dependence (17%). This finding underscores the pivotal role of liquidity risk as the starting point of risk cascades that may lead to financial distress. The strong influence of liquidity risk aligns with prior evidence emphasizing liquidity fragility as a fundamental determinant of bank vulnerability, especially in emerging and energy-dependent economies [16, 17]. Similar to our findings, [11] and [25] confirmed that liquidity shocks can trigger broader financial instabilities by undermining capital adequacy and profitability, eventually increasing distress probability.

Additionally, the model positioned credit risk and operational risk at the second level of influence, with high driving power (83% and 67%, respectively) and medium dependence (50%). This placement indicates that while these risks are strongly shaped by liquidity conditions, they also exert significant downstream effects on other dimensions of bank stability. This result resonates with studies highlighting the cyclical interplay between liquidity shortages and credit quality deterioration [12, 13]. When banks face liquidity strains, they often relax lending standards or fail to manage credit exposures effectively, thereby increasing non-performing assets and default risk [5]. Operational risk, including internal process inefficiencies and cyber vulnerabilities, also intensifies under liquidity pressure, as resource constraints weaken internal controls [14, 15]. The integration of operational risk at this level confirms prior calls to broaden financial distress frameworks beyond traditional credit and market risk [3, 10].

At the subsequent level, net working capital to total assets and net profit to total assets were found to be primarily dependent variables, with lower driving power (50%) but very high dependence (100%). This indicates that profitability and working capital are highly sensitive to upstream risk conditions, especially liquidity and credit dynamics. These findings echo evidence from [4] and [26], which showed that key performance indicators, while widely used in distress prediction models, are lagging indicators that reflect the cumulative effects of deeper structural vulnerabilities. The dependent nature of these metrics suggests that while they remain valuable for early warning, proactive intervention requires addressing the underlying risk drivers rather than focusing solely on end-stage financial ratios.

The market risk dimension occupied an interesting position in the model. Although its driving power was moderate (67%) and dependence high (100%), it connected both upstream liquidity risk and downstream performance indicators. This position aligns with [3] and [7], who noted that market volatility not only transmits systemic shocks but also interacts with liquidity gaps to amplify asset devaluation and capital erosion. Market-to-book value fluctuations, identified as influential in this study, confirm [13] and [11] findings that capital markets' perceptions of bank health can accelerate distress cycles once early liquidity and credit signals appear.

Another important contribution of this study is its integration of expert judgment with ISM to validate the conceptual framework. By drawing on the knowledge of senior professionals in banking, finance, and regulation, including Central Bank specialists, the model ensures contextual accuracy for Iran's banking sector. This aligns with [8] and [9], who demonstrated that expert-driven interpretive modeling is effective for complex risk environments where statistical data alone may fail to capture dynamic causal patterns. The hierarchical structure emerging from this consensus-driven process reflects the practical realities of risk transmission in banks operating under macroeconomic volatility and regulatory transition.

The identified dominance of liquidity risk is also consistent with international evidence. In the European Union, macroprudential frameworks have increasingly emphasized liquidity coverage ratios and stable funding requirements to reduce systemic fragility [18]. Research on dual banking systems shows similar patterns; [19] found that liquidity risk interacts with regulatory quality and competition intensity to shape systemic vulnerability. In developing markets such as Tanzania, [22] observed that robust credit risk management cannot fully offset vulnerability if liquidity frameworks remain weak. The convergence of our findings with these studies suggests that while contextual variations exist, liquidity risk remains universally foundational to banking stability.

This study also reinforces the call to integrate macroprudential insights into bank-level risk management. The inclusion of external volatility factors, such as oil price shocks highlighted by [6] and [11], demonstrates that bank-specific resilience cannot be understood in isolation from the broader economy. Similarly, the findings of [3] on shock amplification in interconnected systems and [1] on network contagion highlight why regulators should adopt system-wide stress testing informed by models like ours.

The interplay between governance and risk dynamics also deserves attention. Our model implicitly underscores that mitigating distress requires governance structures capable of monitoring and controlling key drivers. [23] demonstrated that strong corporate governance reduces the probability of distress by improving oversight of credit exposures, while [10] showed that accurate earnings forecasts, often associated with better governance, can serve as an early warning for emerging liquidity or credit shocks. Furthermore, sustainability-oriented strategies, including green banking practices identified by [24], may strengthen stakeholder trust and funding stability, indirectly reducing liquidity-driven vulnerabilities.

Finally, the study advances the methodological dialogue in bank risk modeling by applying Interpretive Structural Modeling within a dynamic and multi-risk setting. Traditional ratio-based and econometric models (e.g., KMV, VaR) have been widely used [4, 7] but often fail to show how risks interact. ISM bridges this gap by clarifying cause-effect pathways, helping practitioners and regulators identify leverage points. Combining ISM with system dynamics, as suggested by [21], could further enhance predictive and scenario-based risk control in future research and policy.

Despite its contributions, this study has several limitations that should be acknowledged. First, the analysis relied heavily on expert opinion to construct and validate the hierarchical model. While experts were carefully selected from both academic and industry backgrounds to ensure credibility, the subjective nature of interpretive inputs may introduce bias and limit replicability across different settings. Second, the study focused on banks listed on the Tehran Stock Exchange and may not fully capture the risk dynamics of smaller or unlisted financial institutions, such as rural credit cooperatives or specialized banks. Third, although the ISM approach effectively identifies structural relationships, it remains a qualitative and interpretive technique; its predictive capability depends on subsequent quantitative validation, which was outside the scope of this research. Additionally, macroeconomic shocks and regulatory reforms were not modeled dynamically but rather embedded through expert insights, which may reduce sensitivity to fast-changing external conditions.

Future studies could expand on these findings by integrating quantitative validation techniques such as structural equation modeling (SEM) or system dynamics simulation to test the predictive accuracy of the hierarchical risk model under different economic scenarios. Cross-country comparative studies could also help refine and contextualize the model by analyzing whether similar risk structures apply in other emerging economies with different regulatory frameworks and market conditions. Another promising avenue is the integration of real-time market and sentiment data, such as global financial stress indexes and big data analytics, to enhance the model's responsiveness to external shocks. In addition, the influence of new digital banking technologies and fintech innovations on liquidity, operational, and cyber risk layers warrants systematic exploration, especially given the increasing digitization of financial services. Finally, future research could examine the role of green finance and environmental risk exposures, extending the model to capture sustainability-driven dimensions of bank resilience.

For banking practitioners and regulators, the model provides actionable insights for strengthening risk governance and crisis preparedness. Banks should prioritize building robust liquidity management frameworks, including enhanced liquidity buffers, diversified funding strategies, and regular liquidity stress testing. Strengthening credit risk assessment and provisioning standards remains critical, particularly in the context of liquidity-induced credit deterioration. Operational resilience programs, including investment in secure digital infrastructure and internal control systems, should be accelerated to reduce vulnerability when resources tighten. Regulators can leverage the hierarchical model to design macroprudential policies that focus on systemic liquidity safety nets and sector-wide early warning indicators. Furthermore, boards and risk committees should integrate these hierarchical insights into strategic planning and capital allocation to reinforce long-term financial stability.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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