Providing a Continuous Risk-Monitoring Model in the Banking Sector Based on Grounded Data

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Abstract

The purpose of this study is to present a model for continuous risk monitoring in the banking sector based on grounded data. The damage resulting from the non-payment of the principal or interest of a loan is referred to as credit risk. Collateral and guarantees in debt contracts play several roles, including protecting the interests of lenders in the event of default. Moreover, collateral helps improve lending conditions by reducing moral hazard and information asymmetry between lenders and borrowers. In the meta-synthesis stage, a theoretical–deductive analysis is conducted as the first step in the multi-grounded theory approach. The objective of this step is to identify valid, credible, and relevant documents within an appropriate time frame. To this end, articles, books, and reputable national and international organizational websites were reviewed. The first step in meta-synthesis involves formulating the research questions based on the dimensions of grounded theory. In the second step, the researcher systematically searches published articles in reputable domestic and international scientific journals to determine valid and credible documents within the appropriate period. Initially, relevant keywords—individually or in combination—were examined in both Persian and English for the years 2013 to 2024, and for English-language articles for the years 1980 to 2023. Ultimately, 34 articles were identified. The research data were analyzed using a coding method, and the main categories and concepts were extracted. A conceptual model was developed through which the components related to continuous risk monitoring in the banking sector were identified. Based on this model, the most important causal conditions that may influence banking-sector risk include market risk, credit risk, liquidity risk, operational risk, currency risk, interest rate risk, and strategic risk. The research model showed that continuous risk monitoring in the banking sector may lead to consequences such as communication and access to information issues, information technology and system failures, public security breaches, challenges in obtaining long-term financing, reduction in the value of the credit portfolio, and decreased customer and investor trust.

Keywords: *Continuous monitoring, banking sector, grounded data*

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1. Introduction

In contemporary banking systems, the complexity, interaction, and acceleration of financial risks have transformed risk management from a supportive organizational function into a strategic necessity. Banks, as the central pillars of financial intermediation, operate in an environment characterized by uncertainty, competitive pressures, technological disruptions, and regulatory tightening. This dynamic environment demands not only accurate risk identification but also continuous, data-driven monitoring frameworks capable of predicting emerging vulnerabilities before they escalate into systemic threats. The increasing frequency of operational failures, credit defaults, liquidity shortages, and market volatilities in global and regional banking systems demonstrates that traditional static and periodic monitoring mechanisms are no longer sufficient. Consequently, a shift toward predictive, integrative, and automated risk-monitoring architectures has become indispensable [1].

One of the foundational risk categories affecting banks is credit risk, which remains the most influential driver of bank instability and performance degradation. Empirical studies show that determinants of credit risk extend beyond borrower characteristics to include market structure, economic cycles, collateral design, and managerial decisions [2]. Prior evidence indicates that relationship banking, collateral policies, and crisis conditions jointly shape the patterns of credit risk formation in small and medium-sized enterprises, thereby influencing banks' aggregate credit exposure [3]. In addition, credit risk interacts with liquidity risk in ways that amplify the likelihood of bank default unless moderated by strong managerial capabilities and structural safeguards [4]. As banks expand their lending portfolios, the probability of credit risk contagion increases, especially in markets characterized by high uncertainty and limited transparency [5]. These findings reinforce the need for continuous credit-risk monitoring systems that can detect early warning signals and adjust risk-management strategies dynamically.

Operational risk is another fundamental concern, given its wide-ranging manifestations—from internal process failures and human errors to governance breakdowns and external disruptions. Rising operational-risk events in global financial institutions are increasingly associated with board composition, managerial oversight, and governance quality [6]. Modern banking organizations have therefore adopted more sophisticated operational-risk assessment models, including the Loss Distribution Approach (LDA), which improves quantification accuracy and enhances regulatory compliance [7]. Recent advances highlight the capability of machine-learning algorithms to predict operational-risk occurrences with higher precision, enabling early detection and preventive interventions that reduce systemic exposure [8]. Integrating these analytical tools into a continuous monitoring framework can substantially strengthen banks' resilience toward internal and external shocks.

Liquidity risk, as documented extensively in the literature, plays a pivotal role in determining bank survival. Liquidity shortages often emerge abruptly due to market stress, asset–liability maturity mismatches, or sudden deposit outflows. Research demonstrates that the interplay between liquidity and credit risk significantly affects banks' default probabilities, particularly in contexts of weak managerial quality or structural inefficiencies [4]. Furthermore, systemic liquidity pressure can propagate across financial institutions, producing cascading effects that threaten macroeconomic stability. This highlights the necessity of a longitudinal, data-based liquidity-risk monitoring system capable of capturing real-time variations in liquidity buffers.

Market risk, introduced through fluctuations in interest rates, exchange rates, and asset prices, has become particularly relevant in an era of increased global financial integration. The global market integration framework illustrates how interconnected financial markets transmit volatility rapidly from one region to another, intensifying exposure for domestic banks and emphasizing the need for a forward-looking approach to monitoring market risk [1]. Exchange-rate and securities-market instabilities further influence systemic risk accumulation and credit-worthiness assessments across the banking sector. Thus, banks require robust analytical mechanisms capable of processing high-velocity data to evaluate market dynamics and adjust their risk positions accordingly.

The institutional environment also plays a critical role in shaping risk dynamics. Shadow banking activities, changes in capital structure, and non-traditional financial intermediaries have influenced how risk is distributed within and beyond the regulated banking system. Studies reveal that shadow banking can elevate banking-sector risk when capital buffers are insufficient or misaligned with asset structures [9]. The interconnectedness between diversification strategies—both in funding sources and asset allocations—and systemic risk explains why banks with broader portfolios may either reduce or intensify risk exposure, depending on their structural and operational design [10]. As such, risk-monitoring models must incorporate the complexity of structural, regulatory, and market-driven influences to remain comprehensive and effective.

Technological advancements have also shaped contemporary risk-management paradigms. The use of machine learning, big data analytics, and artificial intelligence enables banks to detect anomalies, forecast crisis patterns, and classify risk profiles with greater accuracy. Hybrid analytical systems—such as those integrating Random Forest and Recursive Feature Selection (RFRS)—demonstrate significant predictive power in complex classification environments, suggesting strong potential for adaptation in banking-risk diagnostics [11]. Furthermore, risk governance structures influence the effectiveness of technological integration; banks with robust governance frameworks achieve higher risk-management performance by aligning analytical tools with organizational strategy and regulatory expectations [12]. As technological adoption increases, continuous monitoring frameworks must incorporate both digital capabilities and human-centered competencies.

At the same time, risk management is deeply intertwined with the design of organizational processes, including credit evaluation, collateral management, and guarantee structures. Weaknesses in these domains can magnify exposure and reduce banks' ability to recover outstanding claims. Recent studies highlight that designing a comprehensive credit-risk management model requires a pathological approach that identifies structural weaknesses and redesigns collateral and guarantee systems accordingly [13]. Similarly, the measurement of credit risk and capital adequacy varies substantially across banks depending on size, ownership structure, and methodological orientation, further confirming the need for unified monitoring standards that are continuously updated using real-time information [14].

Broader macroeconomic and geopolitical factors—such as economic instability, inflationary pressures, global shocks, and political uncertainties—exert substantial influence on banking performance and risk formation. Literature shows that these systemic conditions directly affect lending behavior, asset valuation, liquidity flows, and operational resilience. Structural changes in the financial landscape, influenced by international policies and economic integration, require banks to maintain adaptive monitoring systems that track external vulnerabilities alongside internal risk indicators [15]. By integrating macro-level and micro-level risk drivers, banks can strengthen their capacity to anticipate, absorb, and mitigate risk exposure.

New methodological contributions also emphasize the relevance of comprehensive risk-management frameworks built upon multi-case studies and validated through empirical evidence. For instance, integrated models for implementing enterprise-wide risk management outline critical stages such as risk identification, measurement, aggregation, mitigation, and reporting—each of which requires continuous monitoring supported by accurate and timely data [16]. As banks evolve from traditional compliance-based risk management to proactive and strategic frameworks, the role of continuous monitoring becomes increasingly prominent.

Given that risk is multi-dimensional, adaptive, and context-dependent, a holistic monitoring system must incorporate credit, market, operational, liquidity, strategic, and environmental risk components while also accounting for behavioral, institutional, and technological influences. Existing research consistently highlights gaps in risk-monitoring models, particularly with respect to psychological, human-resource, and organizational-behavioral determinants that shape risk-taking and decision-making within banks [17]. When these dimensions are not systematically monitored, banks may overlook early indicators of internal vulnerabilities that later manifest as financial crises.

Despite this extensive body of research, a clear challenge remains: few studies have attempted to synthesize multi-dimensional risk factors into a unified, data-driven framework for continuous risk monitoring specifically tailored to the banking sector. Although valuable insights exist across various strands of literature, they often focus on isolated risk dimensions or rely on static evaluation methods that fail to reflect the dynamic and evolving nature of banking operations. What is needed is a model that not only integrates diverse risk categories but also establishes continuous feedback loops driven by real-time data and empirical validation.

Accordingly, the present study seeks to address this gap by developing a continuous risk-monitoring model in the banking sector based on grounded data, informed by meta-synthesis, expert interviews, and analytical coding processes. The aim of this study is to design a comprehensive, data-driven framework for continuous risk monitoring in the banking sector.

2. Methodology

Grounded theory is a method aimed at understanding and interpreting individuals' experiences of events and phenomena within a specific context. This theory is used when numerous unknowns exist, and the researcher—based on participants' experiential understanding of a particular topic—seeks to develop a theory grounded in real data through a procedural and systematic approach consistent with Strauss and Corbin's (1998) work. Therefore, since no established framework exists regarding a continuous risk-monitoring model in the banking sector, this study seeks—using grounded theory (the reasons for choosing this method are reported later)—to present a model for understanding and interpreting individuals' experiences related to *continuous risk monitoring* within the existing professional banking context, which possesses unique characteristics in terms of governance structure, governing regulations, professional structure, and the nature of banking practice.

Consequently, this study is cross-sectional in terms of time, as interviews were conducted in 2024. From the perspective of purpose, it is exploratory due to the following reasons:

1. No study has yet been conducted in the country on developing a model for continuous risk monitoring in the banking sector using grounded theory.
2. The findings of this study lead to the development of a model.
3. The results expand existing knowledge in the field of risk.

This study is qualitative in terms of the implementation process (type of data), because in this research approach, the first component (data) is collected from various sources such as interviews and documentary studies; in this study as well, data were collected through interviews. Additionally, in qualitative research, the second component includes analytical and interpretive methods used to derive findings or theories. These methods involve conceptualizing data, known as *coding*. In this study, open, axial, and selective coding methods were used. The third component of qualitative research consists of written reports, diagrams, visual models, or oral presentations; in this study, diagrammatic methods were used.

Furthermore, this research is inductive in terms of reasoning logic, because interviewees provide explanations about the outcomes of phenomena based on their own experiences. The inductive nature of grounded theory means that hypotheses are not tested; instead, theory is generated as a result of simultaneous data collection and analysis.

As noted, this study is qualitative and uses grounded data analysis. This method allows the researcher—when hypothesis development is not possible or theoretical coherence regarding the topic is lacking—to construct a new theory instead of relying on pre-existing theories. The new theory is not based on the researcher's personal views but is derived from actual data gathered from real environments and conditions. For this purpose, following the grounded theory approach and the emergent perspective of Glaser (1992), the initial data of this study were collected through unstructured interviews with experts, using an exploratory approach and one broad, open-ended question. Theoretical (snowball) sampling was used, and sampling and interviews continued until concepts and categories reached saturation.

Accordingly, due to the importance of the topic, it was necessary to interview experts who, in addition to possessing multidisciplinary expertise, had comprehensive familiarity with theoretical foundations of continuous risk monitoring and were themselves knowledgeable practitioners in the banking profession. Therefore, individuals who previously or currently had work experience and expertise in other relevant domains (such as university faculty members active in the banking sector) formed the statistical population. This included university faculty, employees in banks or their committees, and managers and partners of financial and credit institutions. Some of the initial participants were highly influential decision-makers in their domains; interviews began with them, and as the study progressed and data were gathered and analyzed, further interviews were conducted with other risk-monitoring experts to achieve deeper conceptual clarity.

After each interview, the transcript was carefully analyzed to extract concepts from each sentence. Only after this process was the next interview conducted. This procedure continued until theoretical saturation was reached. Theoretical saturation means that the most recent interviews no longer produce new data and only repeat previous information (Strauss & Corbin, 1998). Therefore, beginning from the sixteenth interview, no new data emerged, and by the eighteenth interview, reasonable certainty regarding saturation was achieved. It is noteworthy that most interviewees had 15 or more years of professional experience in their field and either held doctoral degrees or were doctoral candidates. The average duration of each interview with the auditing and banking specialists was approximately 70 minutes.

The second step is the coding process, based on three levels: open coding, axial coding, and selective coding. During open coding, data are broken down into discrete parts and examined for similarities and differences. These *concepts* are then categorized based on their similarities through a process called *categorization*, where a *category* represents a more abstract concept that forms the building blocks of theory. In summary, the result of open coding is a set of conceptual categories generated from the data. During axial coding, internal relationships are established among the core categories developed during open coding, examined across properties and dimensions. At the end of this stage, categories are classified into causal conditions, intervening conditions, contextual conditions, strategies, and consequences.

In selective coding—the core stage of grounded theory—the grounded theorist writes the emerging theory by establishing relationships between the core category and other categories. The core category in this study is *continuous risk monitoring in the banking sector*.

The first step is to formulate the research questions in terms of "what" and "who" based on the dimensions of grounded theory. In the second step, the researcher conducts a systematic search of articles published in various reputable domestic and international scientific journals, as well as general sources and websites of reputable national and international organizations, with the aim of identifying valid, credible, and relevant documents within an appropriate time frame. To this end, related keywords were first examined individually and in combination in Persian and English for the years 2013 to 2023, and for English-language articles for the years 1980 to 2023, and ultimately 52 articles were identified. In the third step of the search process, the researcher considers various parameters such as title, abstract, content, article details (author name, year), and so on, and eliminates articles that are not aligned with the research questions and objectives. The inclusion and exclusion criteria for the studies consist of research language, study period, study conditions, study population, and type of study. Considering these criteria, 34 articles were selected to identify the pattern of tax non-compliance, and based on the critical appraisal method, the study entered the fourth stage, namely extracting information from the texts. This appraisal method is regarded as a critical criterion for determining the methodological quality of the reviewed studies, examining them in terms of ten characteristics. Using the ten criteria listed below, and with the assistance of five panel members in the qualitative section, the components related to improving the research variables are determined. This method uses a 50-point scale, and the researcher, based on the scoring system, eliminates any article that scores below 30. This scheme is an index that helps the researcher determine the rigor, validity, and importance of the qualitative studies under review. Therefore, related studies must first be identified using the scoring method based on Table 1, and then the components related to the core categories of grounded theory in continuous risk monitoring in the banking sector must be specified.

Table 1. Critical appraisal of studies

Category	Study location	Type	Authors (Year)	Research objectives	Logic of research method	Research design	Sampling	Data collection	Reflexivity	Ethical considerations	Accuracy of analysis	Theoretical clarity of findings	Research value	Total score
Core phenomenon	Foreign articles	Article	Jabali (2022)	4	5	5	5	3	4	3	4	5	5	43
		Article	Jabali Dezgodoudi (2022)	4	4	5	4	5	4	5	5	4	5	45
		Article	Ahmad et al. (2021)	4	4	4	4	5	4	4	5	4	4	42
		Article	Safiollah and Shamseddin (2020)	4	5	4	4	3	4	4	3	5	4	39
		Article	Da Silva and Dineo (2016)	5	5	5	4	4	5	5	4	5	5	47
		Article	Meisman (2015)	4	3	4	4	3	4	5	3	4	4	38
	Domestic articles	Article	Mohammadi et al. (2023)	3	3	2	1	2	2	2	2	2	2	21
		Article	Taleblou et al. (2022)	2	2	2	2	2	3	2	3	3	3	24
		Article	Heydarzadeh-Moghaddam et al. (2021)	4	3	3	3	4	4	4	4	4	5	38
		Article	Erfannian (2021)	4	3	3	3	3	4	3	4	4	5	36
		Article	Shekarkhah et al. (2021)	4	4	3	5	3	4	3	5	4	5	40
		Article	Sadeghi-Shahdani et al. (2022)	5	4	3	5	5	4	3	4	4	5	42
Causal conditions	Foreign articles	Article	Khan and Ahmad (2012)	5	4	3	4	4	4	4	3	4	5	40

		Article	Mohammad bin Abdullah (2011)	5	5	4	5	4	4	5	4	5	4	45
		Book	Deloitte (2010)	5	5	4	5	5	5	5	4	5	4	47
		Book	Cheninan et al. (2015)	5	5	4	5	5	4	5	4	5	4	46
		Article	Valders et al. (2018)	4	3	3	3	3	4	3	4	3	3	33
	Domestic articles	Article	Barzegar et al. (2023)	5	4	3	4	3	4	4	4	4	5	40
		Article	Elahi et al. (2023)	5	4	3	4	3	4	3	4	4	5	39
		Article	Pendar and Veysi (2020)	4	4	3	4	3	4	3	4	4	4	37
		Article	Sadeghi-Omarabad and Yazdani (2020)	4	4	5	4	3	3	3	4	5	4	39
		Article	Mostafaei-Dolatabad et al. (2018)	4	4	3	4	3	3	4	4	3	4	36
		Article	Rostami et al. (2017)	5	4	5	4	3	4	3	4	3	5	40
		Article	Mehrabi and Nadri (2016)	3	4	3	4	4	3	4	3	3	4	35
Contextual and intervening conditions	Foreign articles	Article	Karavas (2022)	5	4	4	3	3	4	5	4	4	5	41
		Article	Falderson et al. (2022)	5	4	4	4	5	4	5	5	4	5	45
		Article	Kalbri et al. (2018)	4	3	4	3	4	5	3	4	3	5	38
		Article	Chen et al. (2014)	4	5	4	4	3	4	3	4	5	4	40
	Domestic articles	Article	Haghighi-Kaffash et al. (2016)	4	3	4	4	3	4	3	4	5	4	38
		Article	Bazaei and Rezaeian (2015)	4	3	3	4	3	4	4	3	3	4	35
		Article	Jafari and Jalili (2015)	3	2	3	4	4	3	3	4	3	4	33
Strategies and consequences	Foreign articles	Article	Halkebon (2020)	5	4	4	3	4	4	5	4	5	4	42
		Article	Montero et al. (2018)	4	5	4	4	5	4	4	5	4	4	43
		Article	Barrow (2018)	4	3	4	4	3	4	3	4	5	4	40

At this stage, after scoring the studies, they are classified into the following levels: excellent (41–50), very good (31–40), good (21–31), average (10–21), and weak (0–10). Based on the results of the critical appraisal stage of the reviewed studies, 2 articles that did not reach the minimum acceptance score were excluded from further analysis.

The extraction of information in this stage is carried out in two phases. In the first phase, the researcher continuously reviews the selected and finalized articles from Step Three (critical research appraisal) in order to identify the subcomponents and indicators of the study. The initial checklist was prepared based on the identified sources, including the author's name and the year of publication.

Table 2. Determining the Main Components Based on the Meta-Synthesis Approach

Study	CAUS 4	CAUS 3	CAUS 2	CAUS 1	CORE 4	CORE 3	CORE 2	CORE 1	CC 4	CC 3	CC 2	CC 1	IF 5	IF 4	IF 3	IF 2	IF 1
Jabali (2022)		*	*	*	*		*	*						*			*
Jabali Dezgodoudi (2022)		*			*	*	*	*	*			*		*	*		
Ahmad et al. (2021)		*		*	*		*			*	*			*	*	*	*
Safiollah & Shamseddin (2020)					*	*	*	*		*				*	*		
Da Silva & Dineo (2016)				*	*	*	*		*	*		*	*	*	*	*	*
Meisman (2015)				*	*	*	*	*		*	*			*	*		*
Mohammadi et al. (2023)			*		*	*	*	*		*				*	*		*
Taleblou et al. (2022)			*	*	*	*	*			*	*	*	*	*	*	*	*
Heydarzadeh-Moghaddam et al. (2021)	*			*	*	*	*	*		*				*	*	*	
Erfannian (2021)				*	*	*	*	*		*	*			*	*		
Shekarkhah et al. (2021)					*		*	*						*			
Sadeghi-Shahdani et al. (2022)		*	*	*	*		*		*	*	*	*	*	*	*	*	*
Khan & Ahmad (2012)		*	*	*	*		*		*	*	*	*	*	*	*	*	*
Mohammad bin Abdullah (2011)		*	*			*	*				*			*			
Deloitte (2010)			*							*				*			
Cheninan et al. (2015)					*	*					*						
Valders et al. (2018)						*			*	*							
Barzegar et al. (2023)					*		*							*			
Elahi et al. (2023)		*			*		*		*		*			*	*	*	
Pendar & Veysi (2020)		*				*					*					*	
Sadeghi-Omarabad & Yazdani (2020)	*					*					*					*	
Mostafaei-Dolatabad et al. (2018)						*				*	*						

Rostami et al. (2017)	*							*						*
Mehrabi & Nadri (2016)		*	*	*			*	*		*	*	*	*	*
Karavas (2022)	*	*		*		*		*			*	*	*	
Falderson et al. (2022)		*									*			*
Kalbri et al. (2018)		*			*		*	*			*	*	*	
Chen et al. (2014)	*		*	*		*	*	*			*			
Haghighi-Kaffash et al. (2016)			*	*	*		*	*			*	*		*
Bazaei & Rezaeian (2015)	*	*		*		*		*					*	*
Jafari & Jalili (2015)	*	*												
Halkebon (2020)							*	*	*	*	*		*	

Intervening Factors include failure to conduct liquidity stress testing, labor protests, employee health and safety conditions, human resource training, and violations in the recruitment process. Contextual Conditions refer to borrower risk, exchange rate risk, stock market risk, and loan concentration risk. Core Category components consist of customer acquisition and documentation, legal disputes, outsourcing, and transaction recording and reporting. Causal Conditions include operational risk, liquidity risk, credit risk, and market risk.

3. Findings and Results

In this stage of the study, the findings from previous steps are presented. Using the Shannon entropy method, the number of prior studies relevant to the results of this research is statistically demonstrated. In the Shannon entropy method, the frequency of each identified category must first be determined based on content analysis. The required frequency matrix must then be normalized. For this purpose, linear normalization is used.

The information load of each category must be calculated. The following formula is used for this calculation:

Table 3. Determining the Importance and Emphasis of Previous Studies on the Dimensions of Grounded Theory

Dimension	Indicators	Frequency	Normalization	LNnij	Entropy (Ej)	Importance Coefficient (wj)	Rank
Causal Conditions	Hiring-process violations	12	0.1508	-0.2853	0.2058	0.1123	6
	Human resource training	12	0.0397	-0.1280	0.0924	0.0504	6
	Employee health and safety	10	0.0476	-0.1450	0.1046	0.0571	7
	Labor protests	15	0.0794	-0.2011	0.1451	0.0792	3
Core Category	Market risk	15	0.3659	-0.3679	0.2654	0.3356	3
	Credit risk	13	0.3787	-0.3661	0.2578	0.2233	5
	Liquidity risk	16	0.3171	-0.3642	0.2627	0.3322	2
	Operational risk	13	0.3171	-0.3642	0.2627	0.3322	5
Contextual Conditions	Transaction recording and reporting	11	0.2683	-0.3530	0.2546	0.2552	7
	Outsourcing	13	0.2195	-0.3329	0.2401	0.2407	5
	Legal disputes	17	0.2439	-0.3441	0.2482	0.2488	1

Intervening Factors	Customer acquisition and documentation	10	0.2683	-0.3530	0.2546	0.2552	8
	Stock risk	11	0.1639	-0.2964	0.2138	0.1893	7
	Exchange rate risk	10	0.2787	-0.3561	0.2568	0.2273	8
	Securities risk	17	0.3459	-0.2679	0.2154	0.3376	1
	Loan concentration risk	16	0.2623	-0.3510	0.2532	0.2241	2
	Loan applicant risk	14	0.1311	-0.2664	0.1922	0.1701	4
	Failure to conduct liquidity stress testing	12	0.1639	-0.2964	0.2138	0.1893	6

The importance coefficient of each category must be calculated. Any category with greater information load possesses a higher level of importance. For this purpose, the formula $W_j = E_j / (\Sigma E_j)$ is used.

In this study, to assess reliability, the results were provided to one of the experts so that inter-coder reliability could be evaluated using Cohen's Kappa coefficient. Table (4) represents the agreement table between the coding performed by one expert and the researcher for one of the analyzed texts.

Table 4. Calculation of Cohen's Kappa Agreement Coefficient for Category Coding

	Value	Standard Deviation	Test Statistic Tb	Significance Level
Kappa agreement coefficient	0.725	0.173	4.729	0.000
Number	13			

Given the significance level of less than 5% and the Kappa coefficient value of 0.725, the reliability of the extracted codes is confirmed. It is worth noting that researchers believe that if the Kappa coefficient is above 0.60, it is considered acceptable. Additionally, a significance level below 0.05 indicates the existence of coding consistency between the two evaluated documents.

In the second stage, according to the grounded theory research method, interviews were conducted with academic and banking-sector experts to complete information regarding the components and indicators of the study domain. As shown in Table (5), the selected sample consisted of 15 participants, of whom 9 were university faculty members and 6 were doctoral students.

Table 5. Characteristics of the Selected Research Sample

Description	Pasargad Bank	Islamic Azad University (North Tehran Branch)	Islamic Azad University (Science & Research Branch)	Allameh Tabataba'i University	Chamran Ahvaz University	Row Total
Doctoral Student	1	2	2	0	1	6
Faculty Member	2	2	2	1	2	9
Column Total	3	4	4	1	3	15

With this number of interviews, the researcher determined that the collected information had reached saturation, making further interviews unnecessary. Factors such as time, participant accessibility, and willingness to cooperate were also considered when selecting the sample size.

Data analysis in this study was conducted through coding at three levels: open coding, axial coding, and selective coding. In the first stage (open coding), data were described and categorized. In the axial coding stage, the categories and concepts identified during open coding were restructured and linked to each other. Finally, in selective coding, an analytical model for the comprehensive evaluation of human resource accounting was extracted from within the data.

In grounded theory, data analysis is performed through coding. In the open coding stage—which includes two key activities of conceptualization and categorization—the interview questions were asked as shown in Table (6).

Table 6. Interview Questions

Central Category	Question
Core Category	In your opinion, what stages does the continuous risk-monitoring process in the banking sector include?
Causal Conditions	From a psychological perspective, what factors influence the phenomenon under study?
Intervening Conditions	What factors intensify or weaken the phenomenon under study?
Contextual Conditions	At the macro level, what factors expand or restrict the phenomenon under study?
Strategies	What strategies exist for controlling the phenomenon under study?
Consequences	If the phenomenon is controlled, what outcomes will be achieved?

In this step, all key and significant points of the interviews were assigned appropriate conceptual labels (open coding). Then, these codes were placed into a table. A sample of the most important open codes extracted from the interviews is presented in Table (7).

Table 7. First-Level Coding

Central Category	Key Points	Abstract Concept
Core Category	"Continuous risk monitoring in the banking sector, based on Prospect Theory, is grounded in three key ideas: coding, categorization, and evaluation."	Classification of the continuous risk-monitoring process in banking
	Market risk is an instrument for applying continuous risk monitoring in the banking sector.	Market risk
	In this approach, banks open a separate account for each customer loan in order to individually assess the possible consequences (positive or negative) of each loan payment.	Credit risk
	For banks, liquidity risk arises due to shortages and uncertainty in the bank's liquidity level. Another condition that increases liquidity risk is when the markets in which the bank's resources are placed experience a liquidity shortage. Liquidity risk is intertwined with other financial risks; therefore, its assessment and control are difficult.	Liquidity risk
	Operational risk is generally defined as arising from human errors, unexpected events, or technical failures. This includes fraud (when traders provide incorrect information), managerial errors, and control deficiencies. Technical errors may arise from failures in transaction-processing systems, transfer systems, or other organizational-level issues. Operational failures may trigger market or credit risks—for example, an unexecuted trade due to operational error may generate market or credit risk because the cost depends on market price fluctuations.	Operational risk
Causal Conditions	Based on information obtained about individuals, it may occur that—despite their expertise, technical knowledge, and experience acquired from other organizations—they are not properly assessed or evaluated.	Violation of the hiring process
	Given the dynamic nature of the banking industry, training must always be updated and aligned with international developments. Recruitment, retention, human resource evaluation systems, and career pathways must be transparent and well-defined so individuals can be evaluated based on their abilities. Training must be purposeful so that competencies of selected individuals can be utilized and their career progression facilitated.	Human resource training
	Implementing this system in banks enhances participation of employees at all organizational levels in matters related to health, safety, and environment (HSE). Since human resources are a priority for banks, adopting an integrated HSE management system plays a crucial role in establishing a health-focused organization. The goal is to ensure control over critical risks resulting from organizational, equipment-related, procedural, or operational changes.	Employee health and safety
	To optimize performance and attract specialized human resources, banks must pay adequate attention to employee complaints and professional criticisms.	Labor protests
Intervening Conditions	Cultural conditions may influence decision-making and result in varying choices.	Cultural conditions
	Demographic variables such as age, education, and work experience may influence this bias.	Demographic characteristics
	Increasing the volume and breadth of information can reinforce the bias.	Information volume
	Having adequate information for decision-making increases skill, expertise, and accuracy in judgment.	Sufficient information
	Continuous questioning of beliefs, choices, and judgments is the best tool to bring mental narratives closer to external reality.	Critical thinking
Contextual Conditions	Based on accounting standards and banking regulations, all required information and reports must be recorded and prepared to provide a strong structural foundation for future market and financial developments.	Transaction recording and reporting
	In recent years, outsourcing has become a necessity for organizations. Its advantages include cost reduction, focus on core competencies, leveraging external expertise, improving efficiency, eliminating	Outsourcing

	managerial complications, and sharing risk with suppliers—all of which help organizations operate effectively in today’s dynamic and competitive environment.	
	Banks’ legal claims against natural and legal persons typically relate to loan facilities and repayment. When a borrower fails to repay installments, the bank may use collateral; but if collateral cannot be liquidated, the bank initiates legal action to recover claims.	Legal disputes
	With the expansion of communication networks, customers no longer feel obliged to physically provide information; instead, they obtain required information online or communicate virtually with bank staff.	Customer acquisition and documentation
Intervening Factors	One of the most important criteria in stock selection is the stock price, which contains informational value. Investors use stock prices for financial analysis and decision-making. Understanding factors affecting share prices helps investors make better decisions. Banks and insurance companies face various risks such as credit, market, and liquidity risks.	Stock risk
	Today, banks play a crucial role in national economies—especially in countries like Iran that heavily rely on the banking system. Exchange-rate fluctuations in developing countries, due to underdeveloped financial markets, create conditions for financial crises. Instability in exchange rates and financial markets can negatively affect banking stability.	Exchange-rate risk
	As bank size increases, systemic risk and tail risk decrease, while systemic interconnectedness rises.	Securities risk
	Credit risk arises when a counterparty is unable or unwilling to fulfill contractual obligations. It is assessed through the replacement cost resulting from counterparty default. Losses can occur even before actual default.	Loan concentration risk
	A credit event occurs when a counterparty’s ability to meet obligations changes. Credit risk is one of the most significant risk sources in banks. It arises when borrowers are unable to repay their debts.	Loan applicant risk
	Liquidity risk is one of the most critical risks faced by banks; therefore, banks must have appropriate information systems to measure, predict, and control liquidity risk. Each bank manages liquidity using different tools depending on its structure and activities.	Failure to conduct liquidity stress testing
Consequences	The key issue concerns ownership of private and confidential information—for example, whether banking data belong to the individual or the bank, and whether banks can disclose customer information without consent. Questions also arise about whether machine-only access to confidential electronic data (as used in credit-scoring systems) sufficiently protects privacy.	Communication and access to information
	The development of information and communication technologies in advanced banking systems has pushed other countries' banking sectors toward adopting electronic banking and innovation to improve efficiency.	Information technology
	When pressure on banking systems increases (e.g., due to customer traffic), system failures occur such as Shaparak network interruptions, leading to failed transactions and additional costs for banks.	System failures
	With the expansion of online services in various sectors—including financial and credit services—accurate security solutions are essential to reduce security threats. Information security challenges vary based on stakeholder needs, environmental factors, business models, and risk-tolerance levels.	Public security breach

Table 8. Frequency of Final Open Codes

Code	Final Open Code	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	Total
Core Category	Market risk	1	1	0	1	1	0	1	1	0	1	0	0	1	1	0	9
	Credit risk	1	1	1	0	1	1	1	0	1	1	0	1	1	1	1	12
	Liquidity risk	1	0	1	0	1	1	0	1	1	0	1	1	1	0	1	10
	Operational risk	0	1	0	1	0	0	1	1	0	1	1	0	0	0	1	7
Causal Conditions	Hiring-process violations	0	1	0	1	0	0	1	0	1	0	1	1	0	1	1	8
	Human resource training	1	1	1	1	1	0	1	0	1	0	1	0	1	0	1	10
	Employee health and safety	0	1	1	0	0	1	1	1	0	1	1	1	0	1	0	9
	Labor protests	1	1	1	1	1	0	1	0	1	1	0	1	1	1	0	11
Intervening Factors	Stock risk	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
	Exchange rate risk	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0	12
	Securities risk	0	1	0	1	0	1	1	0	1	0	1	1	0	1	1	9
Strategies	Loan concentration risk	1	1	0	1	1	1	0	1	0	1	1	1	1	1	1	12
	Loan applicant risk	1	0	1	0	1	1	1	1	1	1	0	1	1	1	1	12
	Failure to conduct liquidity stress testing	1	1	1	1	0	0	1	1	0	1	1	0	1	0	0	9
Measures	Technology and infrastructure	1	1	1	1	1	0	1	0	1	1	0	1	1	1	0	11
	Fraud risk	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	14
	Violations in procedures and human resource supervision	0	1	1	0	0	1	1	1	1	1	1	1	1	1	0	11
	Violations in banking processes and implementation	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	13

Consequences	Communication and access to information	0	1	0	1	0	1	1	0	1	0	1	1	0	1	1	9
	Information technology	0	1	1	1	1	0	1	0	1	1	1	0	1	0	1	10
	System failures	0	0	1	0	0	1	1	1	0	1	1	1	1	1	0	9
	Public security breach	1	1	1	0	1	1	1	0	1	1	1	1	1	0	1	12

In this study, the validity of the measurement instrument was determined using an expert judgment approach for face and content validity, based on the views of 5 academic experts. The rating scale ranged from a minimum of 1 to a maximum of 5. The results of this analysis are presented in Table (9).

Table 9. Face and Content Validity of the Interview Protocol

Expert 5	Expert 4	Expert 3	Expert 2	Expert 1	
5	4	4	5	4	Phrasing of questions and items
4	4	4	4	5	Alignment of items with the preliminary model
4	3	5	3	4	Alignment of items with the research themes
4	4	5	5	4	Sufficiency of questions/items for covering the research objectives
4.20	3.60	4.50	4.25	4.25	Mean scores
					Overall mean: 4.15
					Validity coefficient: 0.82

The face and content validity coefficient of the data collection instrument in the interview section was calculated as 0.82 (82%). According to Chin (2001), this value is considered acceptable. Therefore, the validity of the instrument is supported.

To assess the reliability of the interview protocol, the “percentage agreement between two coders” method was used. First, a research colleague with experience in qualitative data coding and innovation was invited to collaborate in the study. From among the interview transcripts, the first, fifth, thirteenth, and fifteenth interviews were selected and coded independently by two coders (the researcher and the research colleague). In each interview, codes judged to be the same by both coders were labeled as “agreement,” and differing codes were labeled as “disagreement.” Then, the researcher and the colleague jointly coded the four interviews, and the intra-topic agreement percentage—used as a reliability index for the analysis—was calculated using the following formula:

Percentage of intra-topic agreement = (2 × number of agreements) / (total number of codes) × 100

The results of this assessment are presented in Table (10).

Table 10. Reliability Assessment of the Interview Protocol

Reliability Coefficient	Selected Interview
0.83	First selected interview
0.74	Fifth selected interview
0.71	Thirteenth selected interview
0.73	Fifteenth selected interview
0.75	Overall

Based on this assessment, the reliability coefficient for the qualitative data collection instrument (interview protocol) in this study was 0.75, which is considered an acceptable level of reliability by researchers. Generally, a reliability coefficient above 0.60 is regarded as satisfactory for evaluating this psychometric property of a data collection instrument.

At this stage, based on the information obtained from the first data collection phase (meta-synthesis approach) and the first part of the second data collection phase (open codes from semi-structured interviews), the open codes derived in these two stages were revised, deleted if necessary, and categorized.

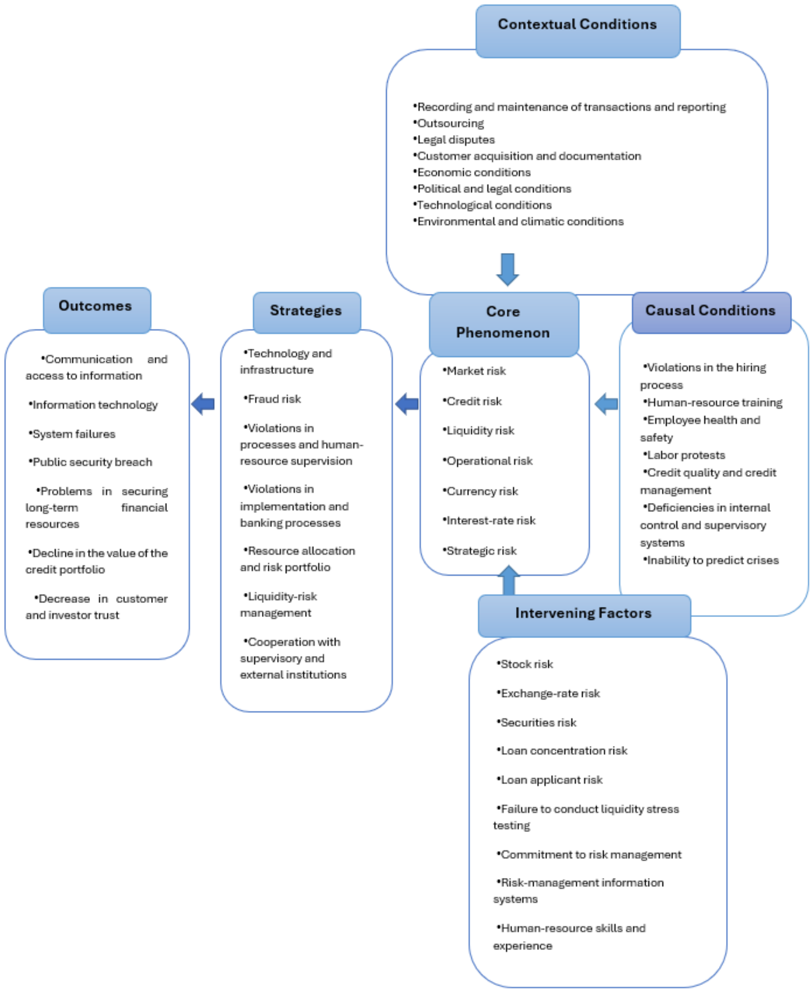

Figure 1. Final Model of the Study

4. Discussion and Conclusion

The findings of this study offer a comprehensive and integrated understanding of continuous risk monitoring in the banking sector by drawing on empirical evidence, expert insights, and grounded-theory analysis. Overall results indicate that risk in the banking system emerges through a multilayered interaction of causal conditions, contextual structures, intervening mechanisms, and strategic responses. The grounded model shows that market risk, credit risk, liquidity risk, operational risk, exchange-rate risk, interest-rate risk, and strategic risk function as dominant causal factors driving risk escalation in banking operations. These results align strongly with current empirical literature, which consistently recognizes the interconnectedness of these risk categories in generating financial vulnerabilities. For example, the identification of credit risk as a central component in this study directly corresponds to extensive international findings showing that credit defaults and borrower-related uncertainties remain the largest contributors to instability in commercial banks [2, 3, 5]. Moreover, the prominence of liquidity risk in the model is consistent with research demonstrating that liquidity shortages, especially when combined with credit deterioration, significantly elevate the likelihood of bank failure [4].

The results indicate that operational risk arises predominantly from human error, process deficiencies, and technological failures, confirming a pattern widely reported in international research. Studies highlight how governance structures and board composition directly influence the occurrence of operational-risk events, validating the strong relationship identified in this research between systemic oversight quality and operational vulnerabilities [6]. In alignment with findings reported by Mor-Valencia and

Zapata-Jaramillo, the model shows that banks rely heavily on structural approaches such as the Loss Distribution Method to classify and predict operational-risk exposures, further supporting the need for continuous, data-driven monitoring rather than periodic evaluation [7]. Likewise, the finding that technological complexity and information-system failures act as significant contributors to risk echoes the evidence showing that risk-monitoring effectiveness is strongly mediated by technological infrastructure and governance [12].

From a strategic perspective, the present findings highlight that banks require robust risk-governance and infrastructure systems, including technologically integrated platforms for early detection, scenario analysis, and cross-risk interactions. The empirical literature supports this conclusion. For instance, studies examining risk-governance frameworks in ASEAN banking systems have shown that stronger governance mechanisms substantially enhance the effectiveness of overall risk management [12]. Similarly, research focusing on enterprise-wide risk-management implementation has emphasized the critical role of technological competency, managerial capability, and data integration for building proactive and adaptive risk-management systems—components that were independently validated through participants' narratives in this study [16]. The convergence between empirical evidence and grounded data suggests a strong consensus regarding the fundamental necessity of structural, technological, and human-resource-based reinforcements in modern risk-monitoring models.

The results also show that several contextual conditions, including transaction-recording quality, outsourcing processes, legal disputes, and customer documentation systems, significantly shape the risk environment. These contextual factors complement and reinforce the core risk dimensions. This is consistent with research suggesting that risk formation in banks is not merely an outcome of financial metrics but also an outcome of institutional structures and procedural reliability. In particular, studies examining the effects of shadow banking, capital structure, and financial opacity have shown that risk formation is amplified when institutional and operational structures lack transparency and alignment [9]. The findings here similarly demonstrate that incomplete documentation, legal uncertainties, and fragmented operational processes heighten exposure to risk and diminish banks’ ability to respond quickly to emerging threats.

Intervening conditions identified in this study—including stock-market volatility, exchange-rate fluctuations, securities exposure, loan concentration, borrower risk, and inadequate liquidity stress testing—reinforce the multi-dimensional character of risk. These moderating mechanisms were found to intensify or attenuate the impact of core risk categories depending on environmental, behavioral, or structural conditions. For example, the study supports the empirical premise that exchange-rate instability, particularly in financially underdeveloped markets, significantly contributes to systemic risk accumulation, consistent with earlier findings [3]. Moreover, the identification of stock risk and securities risk as influential variables aligns with the broader literature on global market integration, which shows that interconnected markets transmit volatility rapidly and must therefore be continuously monitored using real-time tools [1].

On the human-resource dimension, violations in hiring processes, insufficient training, occupational safety weaknesses, internal protests, deficiencies in credit-quality management, and supervisory-system failures emerged as significant causal conditions contributing to systemic risk. These results confirm and extend current scientific understanding of the role of psychological, behavioral, and organizational factors in risk management. For instance, research emphasizing human-capital readiness and competency has demonstrated that deficiencies in employee training and readiness reduce monitoring effectiveness and weaken risk-resilience capacity [17]. Additionally, studies focusing on credit-quality management and collateral-pathology frameworks have reinforced the importance of human-resource competence and process integrity in mitigating exposure to credit risk [13]. The thematic convergence strongly indicates that banking risk cannot be understood solely through quantitative indicators and must instead incorporate behavioral and structural components.

The consequences identified through the grounded model—including communication failures, information-technology disruptions, system breakdowns, public-security vulnerabilities, difficulties in securing long-term funds, credit-portfolio depreciation, and declining customer and investor trust—correspond closely to those reported in previous empirical investigations. Research shows that inadequate information-management systems lead to reduced transparency and weakened decision-making capacity, thereby amplifying operational and market risks [14]. Furthermore, systemic failures in technological infrastructure have been repeatedly linked to operational disruptions and reputational damage, supporting the model’s finding that technological reliability plays a foundational role in risk containment [12].

Similarly, the model's identification of credit-portfolio devaluation and erosion of stakeholder trust as key consequences aligns with literature examining systemic-risk propagation linked to asset diversification and funding structures. Research indicates that misaligned diversification strategies and unstable funding sources increase systemic spillover effects, diminishing investor and depositor confidence [10]. The present findings reinforce this argument by illustrating how inadequate monitoring across interconnected risk domains ultimately leads to reputational and financial instability.

Moreover, the integrative structure of the grounded model is consistent with research emphasizing the need for hybrid analytical systems and advanced computational methods in identifying emerging risks. Studies using machine learning and hybrid classification models for risk prediction have demonstrated the value of combining quantitative analytics with structural insights, a principle strongly reflected in the grounded, data-driven approach adopted here [8, 11]. This study therefore contributes to the literature by providing a conceptual framework that effectively synthesizes multiple risk dimensions and their interdependencies.

Altogether, the findings underline the necessity of continuous, data-driven risk monitoring as opposed to traditional periodic evaluations. This continuous model ensures that dynamic fluctuations, inter-risk interactions, and early warning indicators are captured in real time, thereby enabling more accurate forecasting and more timely intervention. Such a model resonates with the broader movement in global risk management toward proactive and preventative frameworks rather than reactive compliance-based approaches.

This study is inherently limited by the qualitative nature of grounded theory, which relies heavily on expert perceptions and interpretive coding. Although multiple checks were employed to enhance reliability and validity, subjective judgment remains a characteristic limitation of qualitative methodologies. The sample size, while sufficient for grounded research, restricts the generalizability of findings to the wider banking industry. Moreover, the study's dependence on expert availability and willingness to participate may have excluded perspectives from other critical stakeholders, such as regulatory authorities or international banking specialists. Finally, the rapidly evolving technological and economic environment means that risk patterns may shift over time, requiring continuous revision of the conceptual model.

Future studies should consider integrating quantitative validation methods, such as structural equation modeling or machine-learning-based predictive analytics, to test and refine the grounded conceptual model statistically. Expanding the sample to include regulators, fintech specialists, and global banking experts would enhance the generalizability of findings. Longitudinal studies could also examine how the proposed risk-monitoring framework performs under changing macroeconomic and technological conditions. Furthermore, cross-country comparative research could reveal how institutional settings influence the applicability of continuous risk-monitoring models.

Banks should adopt integrated risk-monitoring systems that unify credit, operational, market, and liquidity indicators into a continuous data-driven platform. Human-resource development must be prioritized to mitigate organizational and behavioral vulnerabilities. Strengthening technological infrastructure, especially real-time data analytics and cybersecurity systems, is essential. Finally, banks should institutionalize feedback-driven risk governance to ensure that emerging threats are identified early and addressed systematically.

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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