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Article

A Comprehensive Multi-Dimensional Risk Monitoring Model for Illegal Financial Activities

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Abstract: The rapid expansion of internet finance and fintech has introduced increasingly sophisticated illegal financial activities that challenge traditional regulatory frameworks. Existing regulatory approaches often lack the depth and adaptability to effectively identify and manage these evolving risks. This study proposes a comprehensive, multi-dimensional risk monitoring model tailored to detect illegal financial activities, based on four core dimensions: investor behavior, intermediary platforms, investment products, and regional factors. The model integrates six primary and 26 secondary indicators, enabling quantitative assessment of risk levels and early warning detection. By applying this model to empirical data, our findings highlight specific risk drivers and propose policy recommendations aimed at strengthening regulatory measures. This framework provides regulatory bodies with a practical tool for timely intervention, thereby enhancing financial stability and protecting investor interests.

Keywords: Illegal Financial Activities; Risk Assessment; Financial Fraud Detection

1. Introduction

The rapid growth of internet finance and fintech has profoundly reshaped financial markets, introducing new opportunities but also creating sophisticated, often concealed risks that challenge existing regulatory frameworks. In China, recent high-profile cases—such as the Ezubao incident in 2014, which defrauded approximately 900,000 investors of over 50 billion yuan, the 2023 Quanxiangtong investment incident, which resulted in 1 billion yuan in losses and the 2014 Hebei three regions cooperative society incident, which defrauded approximately 100,000 investors of over 8 billion yuan—underscore the severity and scale of illegal financial activities in the digital age. These incidents reveal persistent gaps in regulatory oversight, as current systems struggle to monitor and address the increasingly complex and cross-regional nature of illegal financial activities.

Despite regulatory progress in China, as emphasized by the 20th National Congress of the Communist Party of China and subsequent policy developments, significant challenges remain. Traditional regulatory approaches are often reactive, lacking the adaptability needed for the dynamic landscape of modern financial crime. Emerging illegal schemes frequently exploit digital platforms, evading conventional detection methods and leveraging information asymmetries and market vulnerabilities.

This study addresses these critical gaps by proposing a comprehensive, multi-dimensional risk monitoring model tailored to illegal financial activities. Grounded in financial risk management theory, this model systematically incorporates investor behaviors, intermediary platforms, investment products, and regional factors to enable proactive identification and assessment of high-risk activities. By examining six primary and 26 secondary indicators across these dimensions, our framework enhances early warning capabilities, providing regulatory authorities with a tool to identify risks before they escalate, ultimately supporting financial stability and investor protection.

2. Literature Review

2.1. Definition and Classification of Illegal Financial Activities

Illegal financial activities refer to financial practices that violate national laws and regulations, encompassing actions such as illegal fundraising, financial fraud, money laundering, insider trading, and market manipulation. These activities pose severe risks to financial stability by undermining market integrity and investor confidence. In particular, high-profile cases like the Ezubao incident illustrate the potential for significant financial and social harm.

The literature broadly categorizes illegal financial activities into distinct types based on their operational mechanisms and target demographics. According to Li and Shen [1], illegal fundraising is the most prevalent, often luring investors with unsustainable high returns and resulting in large-scale financial losses. Fang et al. [2] emphasize that such activities frequently exhibit characteristics akin to Ponzi schemes, attracting a substantial number of investors through promises of high interest rates. Furthermore, as Philippon and Thomas suggest [3], advancements in fintech have allowed illegal financial activities to evolve, creating complex digital platforms that obscure regulatory detection.

At the same time, Philippon and Thomas also point out that with the rapid development of fintech, new forms of illegal financial activities have emerged, bringing unprecedented financial risk challenges [4]. Wang et al. [5] discovered that using internet platforms for false advertising and spreading misleading information attracts a large number of investors to participate in high-risk financial products, which often results in broken capital chains and investor losses. Peng et al. [6] noted that the interplay between financial innovation and regulatory policies leads to the continuous evolution of business models in financial activities. Due to the lag in policy-making, it is difficult to respond promptly to emerging risks. These new forms of illegal financial activities are not only more concealed but also increase the difficulty of regulation, further exacerbating financial risks.

2.2. Drivers of Illegal Financial Activities

Illegal financial activities are driven by a variety of factors, including market inefficiencies, regulatory gaps, and the high profit incentives associated with fraudulent schemes. Existing studies identify several key causes:

1) Market Failures and Asymmetric Information: Borio highlights that financial cycles, particularly during economic downturns [7], exacerbate market imbalances, creating opportunities for illegal financial schemes to thrive. Gong and Wang [8] argue that limited market transparency and information asymmetry enable these activities by exploiting investors' lack of knowledge,

particularly in decentralized platforms where risk disclosure is inadequate.

2) Regulatory and Legal Limitations: Regulatory lag is a persistent challenge, as rapidly evolving digital platforms frequently outpace existing legal frameworks. Jiang et al. [9] argue that this regulatory lag creates exploitable loopholes, especially for fintech innovations that lack clear regulatory guidelines. Xiong [10] further notes that, although China's legal system has advanced, certain laws and regulations are outdated, failing to address the complexities introduced by modern financial crimes.

3) Profit Motives and Investor Psychology: The high-profit potential in illegal schemes draws significant participation, often underpinned by cognitive biases and herd behavior. According to Bushman and Williams [11], the allure of high returns drives investors into high-risk schemes, sometimes despite an awareness of associated risks. This phenomenon is exacerbated by the "Greater Fool Theory," where investors assume they can sell to another buyer before the scheme collapses.

4) Financial Accessibility Limitations: Yang and Huang [12] found that compared to large enterprises, small and medium-sized enterprises (SMEs) and individual investors face more difficulties in obtaining formal financing. Financial accessibility is one of the driving factors of illegal financial activities. Liang and Jiang [13] further demonstrated this by analyzing over 7,000 cases of pyramid schemes, showing a close relationship between the channels of financial resource acquisition and the spread of illegal financial activities.

5) Limitations in Regulatory Resources: Resource constraints in regulatory agencies further exacerbate challenges in effectively monitoring illegal financial activities. Buchak et al. [14] discuss how technical and personnel limitations restrict regulators' ability to employ advanced monitoring techniques, allowing many schemes to operate undetected for extended periods. Shi [15] suggests that while improvements have been made, particularly in preventive oversight, substantial gaps remain in enforcement capacity and technology adoption.

2.3. Risks and Impacts of Illegal Financial Activities

Illegal financial activities have widespread implications for both financial markets and the broader economy, manifesting in several ways:

1) Investor Losses and Market Disruption: Illegal schemes disproportionately affect small and medium-sized investors who lack financial literacy and risk awareness, making them particularly vulnerable. Hu and Wu [16] observe that illegal fundraising and fraudulent schemes primarily target these investor groups, often leading to devastating personal losses. Zhang et al. [17] further highlight that low levels of financial literacy and risk awareness among small investors contribute to the success of these schemes.

2) Systemic Risk to Financial Stability: By distorting normal market operations, illegal financial activities introduce systemic risks that threaten market efficiency and stability. Xu [18] notes that market manipulation and insider trading create artificial price fluctuations, disrupting asset pricing mechanisms and damaging market confidence. Additionally, Guo and Zhao [19] as well as Zhou and Wang [20] suggest that these activities can have a contagion effect, potentially triggering chain reactions that undermine the stability of the entire financial system. This could make the financial system more vulnerable to external shocks [21-22] .

2.4. Current Approaches to Prevention and Monitoring

Recent studies not only highlight the importance of financial education in enhancing public risk awareness and prevention capabilities but also emphasize the potential of emerging technologies, such as artificial intelligence (AI) and big data analytics, in improving early detection and monitoring:

1) Importance of Financial Education: Liu [23] emphasizes that disseminating financial knowledge and enhancing the public's ability to identify and prevent risks is a key approach to reducing the risks of illegal financial activities. Zhu [24] also argues that in the context of the rapid development of internet finance, strengthening financial education for small and medium-sized investors is particularly important. This helps to increase investors' risk awareness and reduce the success rate of illegal financial activities.

2) AI and Big Data in Risk Detection: Zhao [25] discusses how AI-driven algorithms can analyze vast amounts of data, identifying suspicious activities with greater precision and speed compared to manual review methods. This shift toward technology-enabled surveillance represents a significant enhancement in the monitoring capabilities of regulatory bodies.

3) Challenges in Implementation: However, Bai [26] points out that regulatory frameworks must be adapted to effectively integrate these technologies. He argues that without clear legal guidelines on data use and privacy, AI and big data may face obstacles in full deployment. Additionally, a lack of skilled personnel to manage these technologies continues to impede their widespread adoption, particularly in emerging markets.

2.5. Summary and Research Gaps

In summary, while extensive literature has explored the definition, causes, and impacts of illegal financial activities, significant research gaps remain in real-time risk assessment and early monitoring. Current methods lack adaptability to the digital complexities of modern financial schemes. This study seeks to address these gaps by developing a multi-dimensional, indicator-based risk monitoring model, specifically designed to detect illegal financial activities across various dimensions. By combining insights from investor behavior, intermediary platforms, product attributes, and regional indicators, this model aims to improve the regulatory response to evolving financial risks.

3. Indicator System for the Risk Monitoring Model

This study establishes a monitoring model based on a multi-dimensional indicator system to identify and assess the potential risks associated with illegal financial activities. This section details the design of the model's indicators and the normalization process, ensuring consistency and comparability across different indicators.

3.1. Design of the Indicator System

A robust system to monitor illegal financial activities is vital for managing financial risks. Building an effective model requires analyzing key risk factors and measuring indicators based on solid evidence. However, current research on monitoring models for illegal financial risks has notable gaps, limiting their ability to provide precise early warnings.

The accumulation of illegal financial risks often follows recognizable patterns. In recent years, several prominent cases of illegal financial activities, such as Ponzi schemes and the Ezubao incident, have demonstrated that certain indicators exhibit clear abnormalities before significant losses occur. If these potential risks can be identified in a timely manner and the dynamic changes in illegal financial risks monitored in real time, it will help prevent the escalation of financial losses and reduce the costs associated with risk management. Therefore, high sensitivity to abnormal indicators is critical.

The monitoring system for illegal financial risks incorporates a range of key risk indicators. Based on the specific characteristics of illegal financial risks in China, and through an analysis of various risk factors and regulatory practices, this study selects representative indicators by examining major risk events from recent years. The indicator selection process focuses on areas where risks have been particularly pronounced, including illegal fundraising, financial fraud, and insider trading.

To construct a comprehensive framework for monitoring illegal financial risks, this study integrates research insights across four dimensions: **investor behavior** [5], **intermediary platform characteristics** [1,9], **investment product attributes** [2], and **regional characteristics** [27].

Research demonstrates that a platform's operational practices and the profiles of its senior management significantly influence its compliance and regulatory adherence. Similarly, the promotional strategies and intrinsic attributes of investment products substantially impact the legality and compliance of financial activities. Based on these insights, this study develops a framework comprising primary indicators across four dimensions — investors, intermediary platforms, investment products, and regional characteristics—further refined into 26 secondary indicators to enhance early warnings for illegal financial risks (see Table 1). Timely identification of abnormal indicators and prompt intervention can stabilize volatile metrics, thereby preventing potential illegal financial risks from evolving into actual losses.

Table 1. Indicator System for Illegal Financial Activities Risk.

Perspective	Primary Indicator	Secondary Indicator
Investors	Investor Indicators (A)	Speed of investor fund withdrawal (A_1)
		Rating of the investment platform by investors (A_2)
		Whether there are unusual movements in personal accounts (A_3)
		Whether investors collectively petition or file complaints (A_4)
Intermediary Platforms	Platform Indicators (B)	Whether the platform discloses information as required (B_1)
		Whether financial characteristics are normal (B_2)
		Whether there are conflicts of interest (B_3)
		Whether there are abnormal operations (B_4)
		Whether there is negative public sentiment (B_5)
		Platform size (B_6)
		Platform ownership (B_7)
		Net inflow of funds to the platform (B_8)
	Platform Executive Indicators (C)	Average age of platform executives (C_1)
		Average education level of platform executives (C_2)
		Whether platform executives have a bad credit record (C_3)

(Continued Table 1)

Investment Products	Promotion Characteristics Indicators (D)	Whether high returns are promised (D_1)
		Whether capital protection is guaranteed (D_2)
		Whether the use of funds is clearly stated (D_3)
		Whether there is false advertising (D_4)
	Product Attributes Indicators (E)	Whether a single project is repeatedly used for financing (E_1)
		Whether there are a large number of short-term investment targets (E_2)
		Whether the form of the product is inherently risky (E_3)
Regional Characteristics	Regional Indicators (F)	Severity of illegal fundraising in the region (F_1)
		Degree of completeness of the mechanism for handling illegal fundraising (F_2)
		Regulatory strength of the local authorities (F_3)
		Strength of publicity and prevention efforts (F_4)

3.1.1. Investor Indicators

From the perspective of investors, key indicators affecting illegal financial risks include the speed of fund withdrawals, platform ratings provided by investors, unusual activities within personal accounts, and collective complaints or reports filed by investors.

Fund Withdrawal Speed: The rate at which investors withdraw funds reflects the platform's liquidity status. Platforms with faster withdrawal processing generally exhibit stronger liquidity and a greater capacity to handle liquidity risks.

Platform Ratings by Investors: Ratings given by investors can indicate their satisfaction and trust in the platform, serving as a public sentiment indicator related to illegal financial activities.

Unusual Personal Account Activity: Unusual activities in personal accounts, such as sudden, frequent transactions or transfers showing a multiplicative pattern, may signal potential fraudulent actions.

Collective Complaints or Reports: Collective complaints or reports filed by investors reflect their concerns regarding the platform's legality, compliance, and security, serving as an important abnormal public opinion indicator for illegal financial activities.

3.1.2. Platform Indicators

For intermediary platforms, key indicators influencing illegal financial risks include information disclosure, financial health, conflicts of interest, abnormal operational growth, negative public sentiment, scale, ownership, and net fund inflow.

Information Disclosure: This refers to the platform's adherence to regulatory standards set by bodies such as the Securities Regulatory Commission. Compliance with disclosure requirements helps ensure transparency.

Financial Health: Financial stability can be assessed through metrics like capital adequacy and liquidity ratios, which are also used by banks to gauge risk resistance.

Conflicts of Interest: Conflicts arise if the platform is affiliated with the financing party, guarantor, or third-party custodian, which may increase risk exposure.

Abnormal Operational Growth: Rapid growth in customer or employee numbers over a short period may indicate unsustainable operational practices.

Negative Public Sentiment: Incidents like investor runs, loss of company contact, or executives fleeing with funds contribute to negative sentiment and signal potential financial instability.

Platform Scale and Ownership: Larger platforms or those backed by state-owned or listed companies generally exhibit stronger risk resistance compared to privately held enterprises.

Net Fund Inflow: Significant deviations in net fund inflow from the average may indicate operational instability, impacting platform development.

3.1.3. Platform Executive Indicators

Indicators related to platform executives, such as their average age, education level, and credit history, impact illegal financial risks.

Average Age and Education Level of Executives: According to upper echelon theory, the cognitive abilities and perceptions of senior management influence strategic decisions. Generally, younger executives may have a greater tendency toward risk-taking, while higher education levels correlate with better management performance.

Credit History: Poor credit records among senior management can affect the platform’s credit rating,which in turn influences the platform’s stability and risk profile.

3.1.4. Promotion Characteristics Indicators

Promotion strategies for illegal financial activities often involve promises of high returns, principal guarantees, and vague fund usage, sometimes utilizing exaggerated marketing techniques and false advertising.

High Returns and Principal Guarantees: Some schemes attract investors by promising high returns (over 24%, the legal limit for private lending in China) and principal protection. While financially inexperienced investors may be swayed by these promises, others may invest based on the "Greater Fool Theory," believing they can exit before the scheme collapses.

Lack of Fund Usage Transparency: Illegal financial schemes often obscure their underlying assets, failing to clearly communicate how funds are used, which adds to investor uncertainty.

Exaggerated Marketing: Tactics such as celebrity endorsements, promotional events, and misleading advertising are used to create a false impression of legitimacy and attract investors, inflating trust through deceptive promotion.

3.1.5. Product Attribute Indicators

Illegal financial products often exhibit repeated financing for single projects, a high concentration of short-term investment options, and high-risk activities disguised as financial innovation.

Repeated Financing of a Single Project: Some platforms raise funds repeatedly for the same project by offering different maturity variations, which can lead to increased financial strain and potential capital chain disruptions.

High Volume of Short-term Investment Options: Catering to investors’ preference for liquidity, these platforms offer numerous short-term products, which can mask underlying risk.

High-risk Activities Disguised as Financial Innovation: High-risk ventures are often marketed as innovative financial products, using terms like "crowdfunding," "trust investment," "pre-IPO equity investment," "private lending," and "consumer rebate schemes" to appeal to investors.

3.1.6. Regional Indicators

Given regional differences, the monitoring model must consider local characteristics influencing illegal financial risks, such as the severity of illegal fundraising, the effectiveness of regulatory mechanisms, the strength of regulatory supervision, and the intensity of public education.

Severity of Illegal Fundraising and Effectiveness of Handling Mechanisms: These indicators reflect the level of illegal financial risk within a region, including how effectively illegal fundraising cases are managed.

Regulatory Strength: The strength of regulatory supervision can be assessed through the average time taken from reporting to case resolution and the proportion of cases successfully compensated.

Public Awareness and Prevention Efforts: Regions with robust public awareness campaigns and investor education initiatives generally have higher levels of financial literacy, reducing the incidence of illegal financial activities.

Regional indicators capture the unique characteristics of each locality related to illegal financial risks, providing insights for region-specific policy adjustments to combat illegal financial activities effectively. This study discusses regional indicators separately due to their distinct influence, while the five other dimensions—investor, platform, executive, promotion, and product indicators—are collectively referred to as the "five-aspect indicators."

3.2. Normalization of Indicators for Consistent Risk Assessment

While each category of illegal financial risk indicators provides valuable insights, relying on a single category may lead to an incomplete assessment of the overall risk. Therefore, it is essential to standardize and integrate all indicators to ensure a comprehensive and balanced interpretation of risk. This study applies a normalization process to harmonize indicators with varying units and properties, allowing for consistent comparison across different dimensions. The specific normalization methods used for each of the five indicator categories are outlined in Table 2.

Table 2. Normalization of Five-aspect Indicators.

Secondary Indicator	Processing Method
Speed of investor fund withdrawal	Below average → 1; Otherwise → 0
Rating of the investment platform by investors	Below average → 1; Otherwise → 0
Whether there are unusual movements in personal accounts	Yes → 1; No → 0
Whether investors collectively petition or file complaints	Yes → 1; No → 0
Whether the platform discloses information as required	No → 1; Yes → 0
Whether financial characteristics are normal	No → 1; Yes → 0
Whether there are conflicts of interest	Yes → 1; No → 0
Whether there are abnormal operations	Yes → 1; No → 0
Whether there is negative public sentiment	Yes → 1; No → 0
Platform size	Medium or below → 1; Otherwise → 0

(Continued Table 2)

Platform ownership	Significantly higher/lower than average → 1; Otherwise → 0 [1]
Net inflow of funds to the platform	Significantly more/less than average → 1; Otherwise → 0
Average age of platform executives	Below average → 1; Otherwise → 0
Average education level of platform executives	Below average → 1; Otherwise → 0
Whether platform executives have a bad credit record	Yes → 1; No → 0
Whether high returns are promised	Yes → 1; No → 0
Whether capital protection is guaranteed	Yes → 1; No → 0
Whether the use of funds is clearly stated	No → 1; Yes → 0
Whether there is false advertising	Yes → 1; No → 0
Whether a single project is repeatedly used for financing	Yes → 1; No → 0
Whether there are a large number of short-term investment targets	Yes → 1; No → 0
Whether the form of the product is inherently risky	Yes → 1; No → 0

[1] here, "significantly" means more than or less than 50% of the average, including 50%.

For regional indicators, this study analyzes them separately across four major regions of China: the eastern, central, western, and northeastern regions. According to the classification established by the Chinese government, China's economic zones are divided as follows:

Eastern Region: Includes 10 provinces and municipalities—Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan.

Central Region: Comprises 6 provinces—Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan.

Western Region: Encompasses 12 provinces, autonomous regions, and municipalities —Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Northeastern Region: Includes the provinces of Liaoning, Jilin, and Heilongjiang.

Table 3. Processing Results for Regional Indicators (%).

Region	**Severity of Illegal Fundraising**	**Completeness of Handling Mechanism**	**Regulatory Strength**	**Publicity and Prevention Efforts**
Eastern	49.6	72.08	68.32	66.34
Central	22.61	71.45	84.43	71.19
Western	46.61	75.09	47.5	71.19
Northeastern	18.23	45.64	39.47	66.65

Building on the 2020 measurement results by Li [27] regarding the effectiveness of handling illegal fundraising, this study adjusts the indicator values for consistency in risk interpretation. In Li's study, a lower score for the severity of illegal fundraising indicates a more severe situation. To align with the objective of this paper, where higher scores denote higher risks, we use the transformation (1- indicator value) to reflect increased severity. All indicator values are rounded to two decimal places. The processed values for regional indicators are presented in Table 3.

For indicators representing handling mechanisms, regulatory strength, and publicity efforts, higher scores indicate lower risks. However, since this paper aims to quantify risk magnitude, higher values must correspond to higher risks. Therefore, in calculating regional risks within the model, we apply (1- indicator value) to each of these three indicators to represent their respective risk levels accurately.

4. Construction of the Model

This section outlines the construction of the illegal financial risk monitoring model, focusing on the selection of methods, the weight assignment of indicators, and the model's adaptability to evolving financial risks.

4.1. Method Selection

The Analytic Hierarchy Process (AHP) is chosen as the primary method for assigning weights to the indicators in this risk monitoring model. AHP is highly effective for transforming complex, multi-objective, and multi-criteria problems into a hierarchical structure, making them easier to evaluate as a single-objective problem. This approach addresses the limitations of other weighting methods by incorporating subjective judgments while employing consistency checks to minimize potential biases, thereby enhancing the scientific rigor of the evaluation process.

Given the rapidly evolving financial landscape, new forms of illegal financial activities continuously emerge, necessitating adaptive risk monitoring approaches. The flexibility of AHP allows experts to periodically reassess and update the model by adjusting indicators and re-evaluating their relative importance. This adaptability ensures that the model remains accurately reflective of shifts in illegal financial activities and responsive to changes in the risk environment. Consequently, this study employs AHP to assign weights to various indicators of illegal financial risks, ensuring the model's ongoing relevance and robustness.

4.2. Indicator Weight Assignment

Following the establishment of the indicator system, six experts with relevant domain expertise were invited to conduct pairwise comparisons for the six primary indicators and the 23 secondary indicators across five aspects. Through these comparisons, judgment matrices were constructed, allowing for the calculation of indicator weights using the geometric mean (or arithmetic average) method.

To ensure the consistency and reliability of the expert judgments, the maximum eigenvalue, denoted by λmax, along with the number of indicators n and the random index RI, are used to assess matrix consistency. The specific calculation formulas are as follows:

$$\text{Consistency Index } (CI): CI = (\lambda max - n)/(n\text{-}1) \tag{1}$$

$$\text{Random Index } (RI): RI = \overline{CI} \tag{2}$$

$$\text{Consistency Ratio } (CR): CR = CI/RI \tag{3}$$

If $CR < 0.1$, the consistency test is deemed satisfactory, indicating that the judgments are acceptably consistent. Due to the limited space, this paper only lists the judgment matrix of two of the experts for the main indicators as shown in Table 4-5. The final weights for the primary indicators, calculated using an equal-weighted aggregation of each expert's scores, are displayed in Table 6.

Table 4. Expert 1 Primary Indicators Judgment Matrix.

Indicator	A	B	C	D	E	F	Weight (%)
A	1	1/5	3	1/3	1/5	2	8.13
B	5	1	7	3	1/2	6	29.95
C	1/3	1/7	1	1/4	1/6	1/2	3.86
D	3	1/3	4	1	1/4	3	14.24
E	5	2	6	4	1	5	38.07
F	1/2	1/6	2	1/3	1/5	1	5.75
CR=0.043＜0.1							

Table 5. Expert 2 Primary Indicators Judgment Matrix.

Indicator	A	B	C	D	E	F	Weight (%)
A	1	1/6	1/3	1/5	1/4	3	5.96
B	6	1	5	4	5	7	44.68
C	3	1/5	1	1/3	1/2	2	8.89
D	5	1/4	3	1	4	4	22.54
E	4	1/5	2	1/4	1	5	13.97
F	1/3	1/7	1/2	1/4	1/5	1	3.96
CR=0.093＜0.1							

Table 6. Final Weights for Primary Indicators.

Indicator	A	B	C	D	E	F
Weight W_i (%)	8.05	26.65	5.08	21.3	34.26	4.67

Based on the analysis of the judgment matrices for the primary indicators in the illegal financial risk monitoring model, it was found that **product indicators (E)** carry the highest weight at 34.26%, signifying the strongest influence on illegal financial risks. In contrast, **platform executive indicators (C)** and **regional indicators (F)** have the lowest weights, at 5.08% and 4.67%, respectively, indicating a comparatively minor impact.

The calculation method used for determining the weights of the secondary indicators is identical to that for the primary indicators. The final weights for the secondary indicators within each of the five aspects are summarized in Table 7.

Table 7. Final Weights for Secondary Indicators Across Five Aspects.

Indicator	A	B	C	D	E
Weight （W_{1i}～W_{5i}） %	A_1 (19.83); A_2 (8.09); A_3 (29.93); A_4 (42.15).	B_1 (8.49); B_2 (17.58); B_3 (29.3); B_4 (16.47); B_5 (13.13); B_6 (3.28); B_7 (4.27); B_8 (7.49).	C_1 (15.93); C_2 (25.19); C_3 (58.89).	D_1 (30.00); D_2 (4.84); D_3 (17.93); D_4 (47.22).	E_1 (53.9); E_2 (16.38); E_3 (29.73).

Based on the judgment matrices for investor indicators, this study finds that the primary factors impacting investor risk are collective petitions or complaints by investors, with a weight of 42.15%, followed by unusual movements in personal accounts, with a weight of 29.93%. Together, these two indicators constitute over 70% of the total weight for investor risk indicators, underscoring their substantial influence. For platform risk indicators, the main contributing factors are the presence of conflicts of interest, normalcy of financial indicators, and occurrence of abnormal operations. The combined weight of these three indicators exceeds 60%, highlighting their significant impact on platform risk. Regarding the risk indicators for platform executives, the most critical factor is whether executives have a record of poor credit, carrying a weight of 58.89%

as a single indicator, indicating its prominent role in assessing executive-related risk. For publicity characteristics, the presence of false advertising and promises of high returns are the primary factors, with a combined weight exceeding 70%, marking them as major contributors to publicity-related risks. In terms of product attributes, the key factor is whether the platform uses a single project for repeated financing, which holds a weight of 53.90% as a single indicator, emphasizing its strong influence on product-related risks.

Given the substantial influence of the above indicators, it is essential to prioritize them in the risk analysis process. At the same time, acknowledging the potential for a "butterfly effect," it is important not to overlook indicators with smaller weights, as they may have a significant impact on overall risk assessment under specific conditions.

Table 8. Weights for Regional Indicators W_{6i} (%).

Severity of Illegal Fundraising	Completeness of Handling Mechanism	Regulatory Strength	Publicity and Prevention Efforts
7	27.07	52.39	13.54

For the weights of the regional secondary indicators, this study references the 2020 measurement results on the effectiveness of handling illegal fundraising by Li [27], as presented in Table 8. Additionally, when assessing specific regional risk conditions, it is essential to consider the data provided in Table 3.

4.3. Model Calculation and Risk Scoring

Based on the aforementioned analysis, this paper can derive a monitoring model for illegal financial risk (R), as detailed in equations (4) to (10).

The overall monitoring model for illegal financial risk is:

$$R=W_1\times A+W_2\times B+W_3\times C+W_4\times D+W_5\times E+W_6\times F \quad (4)$$

Where R represents the illegal financial risk; A to F are the primary indicators of illegal financial risk, as detailed in Table 1, and their calculations are given by equations (5) to (10); W_1 to W_6 are the weights corresponding to each primary indicator, as specified in Table 10.

$$A=\sum_{i=1}^{4} W_{1i}\times A_i \quad (5)$$

$$B=\sum_{i=1}^{8} W_{2i}\times B_i \quad (6)$$

$$C=\sum_{i=1}^{3} W_{3i}\times C_i \quad (7)$$

$$D=\sum_{i=1}^{4} W_{4i}\times D_i \quad (8)$$

$$E=\sum_{i=1}^{3} W_{5i}\times E_i \quad (9)$$

$$F=\sum_{i=1}^{4} W_{6i}\times F_i \quad (10)$$

Additionally, W_{1i} to W_{6i} represent the weights corresponding to each secondary indicator, as detailed in Tables 7 and 8.

4.4. Application of the Model

4.4.1. Determination of Warning Thresholds

To establish appropriate warning thresholds, data and case studies were gathered from sources including the Wind Database, Tonghuashun Finance, company websites, regulatory authorities, and China Judgements Online. A sample of five legal financial activities and five illegal financial activities was selected for comparative analysis. The legal financial activities analyzed included products such as Agricultural Bank of China's wealth management products, government bonds, convertible bonds, mutual funds, and stocks. The illegal activities examined included Ponzi schemes, the Ezubao incident, Hebei three regions cooperative society incident, Quanxiangtong investment incident, and the Evergrande Wealth Overcollection Treasure incident.

Using the monitoring model developed in this study, risk levels for each of these 10 financial activities were calculated, as presented in Table 9. In this table, each activity is represented by numbers 1 to 10.

When calculating the risk of illegal financial activities using this model, if a financial product's initial issuance location is confined to one of the four designated regions (eastern, western, central, or northeastern), the model calculates the specific regional risk value for that location. If the issuance location does not fall within these regions, the regional risk value for that product is set to 0.

Table 9. Risk Levels of Financial Activities.

Project	1	2	3	4	5	6	7	8	9	10
Risk Level (%)	5.61	0	19.5	18.47	21.96	94.68	74.12	82.48	77.24	68.13

The analysis reveals that for the five legal financial activities, the risk values calculated by the monitoring model are all below 25%, while the values for the five illegal financial activities exceed 65%, demonstrating a significant disparity between the two groups.

Based on this distinction, a risk threshold of 45% was selected (a midpoint between the 25% and 65% ranges). When the monitoring model outputs a risk value of 45% or higher, a warning is issued, prompting regulators to scrutinize the financial activity's compliance status and take preventive measures to mitigate further risk escalation.

4.4.2. Model Evaluation

Following its construction, the monitoring model was applied to forecast illegal financial risks across the eastern, central, western, and northeastern regions using case data.

It is important to acknowledge the model's limitations. First, the indicator system is primarily based on four dimensions—investors, intermediary platforms, investment products, and regional characteristics—and may overlook other potentially relevant perspectives. Second, the AHP-derived weights are based on expert judgment, which may introduce subjectivity depending on the participating experts' perspectives.

The illegal financial risk monitoring model has two primary functions: to assess trends in illegal financial risks and to identify significant instances of illegal financial activities, thereby enhancing regulatory oversight.

Specifically, the model can be continuously updated through ongoing adjustments to the indicator system and expert re-evaluation, ensuring its relevance in a dynamic risk environment. By inputting relevant case data, the model provides real-time assessments of emerging risks. Additionally, to accommodate advances in fintech, the model can assess risks associated with specific financial innovations, helping regulators to support beneficial innovations while targeting fraudulent schemes that exploit the appearance of innovation. This strengthens the regulatory framework and improves the capacity of local and national governments to prevent and mitigate financial risks effectively.

5. Conclusion

This study presents a multi-dimensional indicator-based risk monitoring model for illegal financial activities, offering a systematic approach to identifying and assessing risks in real time. By integrating diverse indicators across four key dimensions—investor behavior, intermediary platforms, investment products, and regional characteristics—the model provides a comprehensive framework that allows regulatory authorities to detect and respond to potential risks proactively.

The primary contributions of this study lie in its establishment of a comprehensive indicator system, the application of the Analytic Hierarchy Process (AHP) for weighting indicators, and the practical relevance and adaptability of the model. The indicator system was developed based on insights drawn from recent cases, regulatory practices, and expert knowledge, ensuring a detailed approach that addresses the complexity and multi-faceted nature of illegal financial risks more effectively than single-dimension models.

Using AHP to assign weights to these indicators, the model prioritizes the most critical factors in assessing illegal financial risks. This approach allows for periodic updates, enabling the model to remain adaptive in response to changing risk landscapes and evolving forms of illegal financial activities. The practical relevance of the model, along with its flexibility, makes it particularly suitable for use by regulatory authorities and financial institutions in varied contexts. By continuously updating the indicator system and recalibrating expert scores, the model can be adjusted to reflect current trends and emerging risks, providing timely insights for effective regulatory intervention. Furthermore, this study establishes a warning threshold of 45%, based on the distinction between legal and illegal financial activities, which allows the model to issue warnings when a financial activity's risk surpasses this level, enabling regulators to take preventive measures before issues escalate.

While the model offers valuable insights, several limitations should be noted. The indicator system, although comprehensive, is limited to four primary dimensions—investors, intermediary platforms, investment products, and regional characteristics—and may not capture all relevant risk factors. Future research could address this limitation by expanding the indicator system to include additional dimensions, such as behavioral data from social media or blockchain transaction patterns, to enhance the model's accuracy in risk assessment.

Another limitation is the reliance on expert judgment for the AHP-based weighting process. This dependency introduces a degree of subjectivity, as the assigned weights may be influenced by the perspectives and biases of the participating experts. Although consistency checks are applied to mitigate these issues, incorporating machine learning techniques in future research could offer a more objective and data-driven approach to weighting indicators. Additionally, the model's effectiveness depends on patterns derived from historical data on illegal financial activities. As new forms of financial crime continue to emerge, historical data may not fully capture novel risks. To address this, a mechanism for real-time data integration could be developed, ensuring the model remains relevant as risk patterns evolve.

In conclusion, this study presents a structured and adaptable monitoring model for illegal financial activities, grounded in a multi-dimensional indicator system that addresses the complexities of modern financial risks. By integrating insights from various risk dimensions and employing AHP for indicator weighting, the model provides a reliable early warning system that enables regulators to identify potential risks and intervene proactively. Despite its limitations, this model offers a valuable foundation for ongoing research and development in the field of financial risk monitoring, particularly for identifying and managing illegal financial activities.

As the financial sector continues to evolve, this model's flexible design allows it to be updated to reflect emerging risks and technological advancements. Ultimately, the insights and methodologies presented in this study aim to strengthen the capacity of regulatory authorities to prevent and mitigate the impact of illegal financial activities, contributing to a more stable and secure financial environment.

Based on the analysis and conclusions presented earlier, this paper offers the following recommendations:

1) Establish Clear Entry Mechanisms for New Financial Forms.

The rapid advancement of Internet technology has spurred the swift rise of digital payments, internet finance, shadow banking, and equity crowdfunding. However, this progress has also facilitated the innovation of illegal financial activities. Currently, regulatory authorities have not established clear entry standards for these emerging financial models, which could fuel illicit financial risks, endanger financial stability, and impede economic progress. Therefore, defining scientifically rigorous and clear entry rules is a critical measure to ensure economic stability and social harmony.

2) Develop Differentiated Local Regulatory Frameworks

This study identifies multiple influences on illegal financial risks. While existing regulations have had some success in curbing illegal activities, there are still shortcomings in fully mitigating these risks, highlighting the need for more targeted regulation. Local regulatory bodies should integrate comprehensive indicators of illegal financial risks, aligning model-derived risk assessments with the local economic environment. Tailored strategies should focus on rectifying high-risk activities while supporting compliant financial innovations that foster local economic development. Balancing risk management with innovation encouragement is essential to promote a healthy financial ecosystem.

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