



IMPROVING DIGITAL MONITORING AND EARLY WARNING SYSTEMS IN THE MANAGEMENT OF ENTERPRISE FINANCIAL RISKS

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Abstract: *The article examines the theoretical and methodological foundations and practical directions for improving digital monitoring and early warning systems (EWS) in enterprise financial risk management. An integrated indicator system with a traffic-light scale, combining the Altman Z-score and machine learning techniques, is proposed. The findings can be applied by corporate finance departments and by banks in credit monitoring.*

Keywords: *financial risk, digital monitoring, early warning system, Z-score, solvency, risk indicators, machine learning, dashboard.*

Introduction

In the digital economy, the financial stability of an enterprise has come to depend on its ability to detect risk signals in time. Delayed information means a delayed decision: signs of insolvency usually appear earlier in daily cash flow, accounts receivable, and changes in the supply chain than in quarterly reports.

In Uzbekistan, the relevance of this issue is determined by several factors: the rapid growth of the banking sector's loan portfolio, the transformation of state-owned enterprises, the digitalization of tax and reporting processes, and the transition to International Financial Reporting Standards (IFRS). At the same time, in many enterprises risk monitoring still relies on annual or quarterly reports, indicators are not integrated into a single system, and warning thresholds are set subjectively.



LITERATURE REVIEW

The scientific tradition of early detection of financial distress began with the research of W. Beaver (1966), who showed that individual financial ratios (such as cash flow to debt) had discriminating power even five years before bankruptcy [1]. E. Altman (1968) combined several ratios into a single Z-score indicator and proposed a model based on discriminant analysis [2]. J. Ohlson (1980) estimated the probability of bankruptcy using logit regression [3], while T. Shumway (2001) substantiated the superiority of the time-varying model [4].

The second direction relies on market data: R. Merton (1974) created the basis for calculating the probability of default by valuing equity as an option on the firm's assets [5]. At the macroeconomic level, G. Kaminsky, S. Lizondo, and C. Reinhart (1998) developed the "signal approach" and introduced the principle of issuing a warning when an indicator exceeds a threshold value [6]. This very principle underlies enterprise-level traffic-light systems.

In recent years, machine learning (random forests, gradient boosting, neural networks) has significantly improved accuracy compared with classical models; F. Barboza, H. Kimura, and E. Altman (2017) showed that random forest and boosting methods outperform classical models [7]. However, the "black box" nature of such models creates distrust among regulators and management; therefore, interpretable approaches (such as SHAP) are necessary.

At the institutional level, COSO ERM (2017) and ISO 31000:2018 require risks to be linked to strategy, while BCBS 239 (2013) requires accuracy, completeness, and timeliness in the collection and reporting of risk data [8][9][10]. In the local and Russian-language literature (Sheremet, Savitskaya, and others), the main attention is paid to liquidity, financial stability, and profitability ratios, while issues of real-time digital monitoring remain insufficiently developed [11][12].

The table below compares the main approaches.



Table 1. Comparative analysis of approaches to financial distress prediction¹

Approach	Core idea	Advantage	Limitation
Beaver (1966) — single ratio	Predictive power of an individual indicator	Simple, easy to understand	Does not capture complex situations
Altman Z-score (1968)	Discriminant analysis, 5 ratios	Quick to calculate, widely recognized	Static; sensitive to industry specifics
Ohlson O-score (1980)	Logit regression	Provides a probability	Depends on distributional assumptions
Merton model (1974)	Option theory	Uses market information	Not suitable for enterprises not listed on an exchange
Signal approach (1998)	Exceeding a threshold value	Warning-oriented	Subjectivity in choosing thresholds
ML models (2010s)	Nonlinear relationships	High accuracy	Hard to interpret; large data required

Research gap: existing studies have examined classical models, real-time data flows, and ML interpretability separately; their integration within a single digital monitoring architecture at the enterprise level has not been sufficiently addressed. This article aims to fill this gap.

Research methodology

The study used a systems approach, comparative and ratio analysis, expert assessment, scenario modeling, and statistical methods. The information base

¹ Compiled by the author



consisted of enterprises' financial statements, bank statements, ERP/IC data, data obtained from electronic tax and customs systems, and generalized practical observations.

The proposed system consists of five layers: data sources, collection and quality control (ETL), the analytical core, the alert mechanism, and the decision-making layer. An important aspect is feedback rather than a top-down flow: the outcome of each decision is returned to the analytical core for model recalibration.

Data passes through five layers into a decision, and the outcome returns to the model

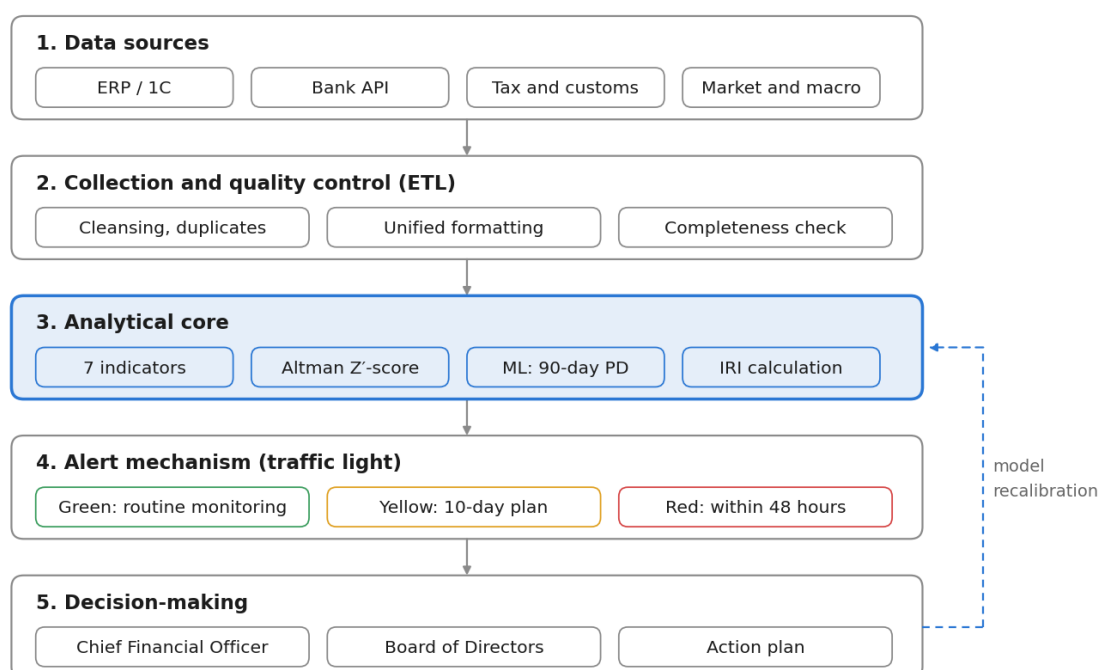


Figure 1. Five-layer architecture of the digital monitoring and early warning system

The indicators are divided into five groups. For each indicator, an update frequency and a three-zone threshold are defined (the recommended values are for an average industrial enterprise; they are adapted according to industry specifics).

Table 2. Indicator system and threshold values



Group	Indicator	Update frequency	Green	Yellow	Red
Liquidity	Current ratio	weekly	> 1.5	1.0–1.5	< 1.0
Solvency	Equity ratio (equity / assets)	monthly	> 0.5	0.3–0.5	< 0.3
Solvency	Net debt / EBITDA	monthly	< 2.5	2.5–4.0	> 4.0
Cash flow	Cash reserve (days)	daily	> 60	30–60	< 30
Cash flow	DSCR (debt service coverage ratio)	monthly	> 1.5	1.0–1.5	< 1.0
Profitability	Return on assets (ROA), %	quarterly	> 5	0–5	< 0
Operational	Share of overdue receivables, %	weekly	< 10	10–25	> 25

Altman Z-score and the integral risk index

For manufacturing enterprises not listed on the market, Altman's modified model is used:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$



where X1 is working capital / assets; X2 is retained earnings / assets; X3 is earnings before interest and taxes / assets; X4 is the book value of equity / liabilities; X5 is sales revenue / assets. $Z' > 2.9$ is the safe zone, 1.23–2.9 is the grey zone, and $Z' < 1.23$ is the distress zone [2].

Because the Z-score relies on annual data and is static, an **integral risk index (IRI)** is proposed to complement it with monthly and weekly indicators:

$$IRI = 100 \cdot \sum_{j=1}^5 w_j \cdot \frac{1}{n_j} \sum_{i=1}^{n_j} \frac{s_{ji}}{2}$$

where s_{ji} is the score of the i -th indicator in group j (green = 0, yellow = 1, red = 2); w_j is the group weight (liquidity 0.25; solvency 0.25; cash flow 0.20; profitability 0.15; operational 0.15); n_j is the number of indicators in the group. The IRI ranges from 0 to 100: the higher the value, the greater the risk.

Hybrid warning logic

Warnings are issued in a three-level (traffic-light) system. The joint state of the IRI and Z' , as well as the 90-day probability of default (PD) calculated by the ML model, are taken into account. When these three signals confirm one another, false signals are reduced.

Table 3. Traffic-light zones and recommended actions

Zone	IRI	Z'	PD (90 days)	Action
Green	< 30	> 2.9	< 5%	Routine monitoring
Yellow	30–60	1.23–2.9	5–20%	Analysis by the Chief Financial Officer; action plan within 10 days
Red	> 60	< 1.23	> 20%	Immediate report to the



Zone	IRI	Z'	PD (90 days)	Action
				Board of Directors; recovery plan within 48 hours

ANALYSIS AND RESULTS

To demonstrate how the system works, a simulation was conducted using 24 months of **illustrative** data for a sample manufacturing enterprise; when real enterprise data are entered, all values will be updated. A delay of more than 60 days in repaying a bank loan was adopted as the default event.

Cash flow and receivables indicators began to deteriorate before balance sheet ratios: by month 12, the cash reserve had fallen from 74 days to 48 days, and the share of overdue receivables had risen from 8% to 15%, while the Altman Z' was still in the grey zone (2.5). In precisely this “hidden” period, conventional quarterly analysis gives no cause for concern.

Table 4. Dynamics of indicators of the sample enterprise

Indicator	Month 6	Month 12	Month 18	Month 24
Current ratio	1.9	1.5	0.95	0.7
Equity ratio	0.56	0.44	0.29	0.21
Net debt / EBITDA	1.9	3.1	4.4	6.0
Cash reserve (days)	74	48	26	9
Overdue receivables (%)	8	15	27	38
Altman Z'	3.1	2.5	1.7	1.0
IRI (0–100)	24	44	72	93

Dynamics of the integral risk index

IRI entered the red zone in month 16: 5 months before the Z' signal, 8 before default

Integral risk index (0-100), monthly; sample manufacturing enterprise, illustrative data

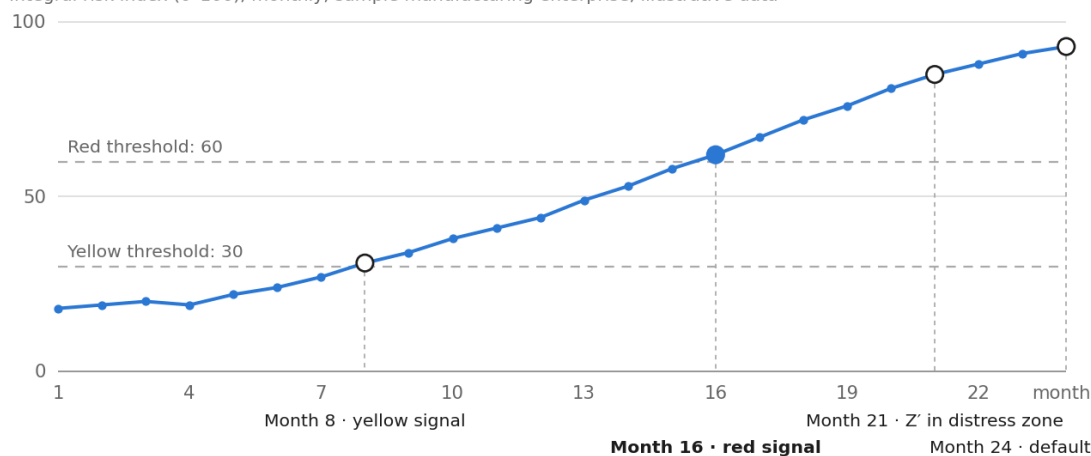


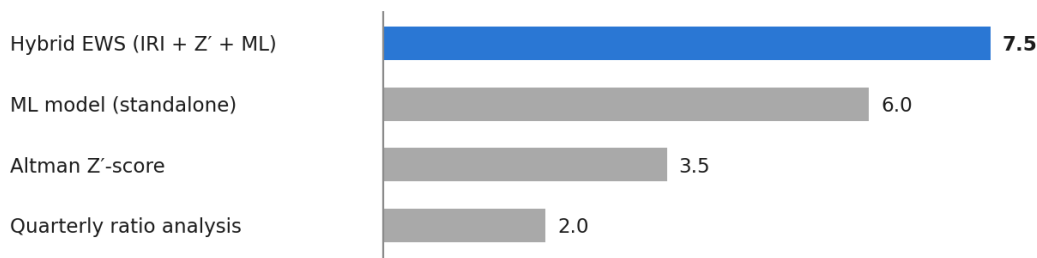
Figure 2. Dynamics of the integral risk index (IRI) over 24 months and signal points.

The IRI crossed the yellow threshold (30) in month 8 and the red threshold (60) in month 16. The Altman Z', by contrast, fell into the distress zone (below 1.23) only in month 21, that is, after the quarterly report was released, with just 3 months left before default. Thus, the red signal was issued 5 months earlier than the Z' signal and 8 months before default; this period is sufficient for debt restructuring, collection of receivables, or raising additional capital.

Comparative effectiveness of methods

The hybrid system signals 5.5 months earlier than conventional analysis

Average lead time from red signal to default, months; sample scenarios



Difference between hybrid and quarterly analysis: 5.5 months

Figure 3. Comparison of different methods by warning lead time

In the comparison, the hybrid system issued the red signal on average 7.5 months before default, while quarterly ratio analysis did so 2 months before. A



standalone ML model also gives an early signal, but because its interpretability for management is low, it makes rapid decision-making difficult.

The hybrid model outperforms classical methods in accuracy (AUC 0.91)

AUC: 1 = perfect separation; sample set, test period

Random guess: 0.50



Figure 4. Comparison of methods by discriminating power (AUC)

The hybrid approach is also superior in discriminating power (AUC 0.91). Importantly, because it requires confirmation by three independent signals (IRI, Z', PD), it reduces the probability of false signals: the red zone is declared only when at least two signals coincide.

Discussion of the results

First, the main value of early warning lies not in accuracy but in **the time available for decision-making**: an 8-month interval makes it possible to carry out not only financial but also organizational measures (reviewing expenses, agreeing payment terms with suppliers). Second, the annual or quarterly Z-score remains the foundation of the system, but applying it without monthly and weekly operational indicators leads to delayed signals. Third, the output of the ML model should be interpreted using methods such as SHAP, that is, presented in the form of “which indicator raised the signal, and by how much.”

Limitation of the study: the results are based on an illustrative simulation. Validating the model in practice requires an observation period of at least 3–5 years and a sufficient sample of enterprises across industries.



Directions for improvement and an implementation roadmap

Improvement should be carried out simultaneously in six directions: limiting the effort to technology alone (dashboard, ML) while neglecting data quality and organizational accountability would make the system ineffective.

Table 5. Directions for improvement

Direction	Key measure	Expected result
Data infrastructure	A single data warehouse; integration of ERP, bank API, electronic invoice, and credit bureau data	Indicators are updated daily/weekly
Methodological	Calibration of thresholds and IRI weights by industry	Signals matched to industry specifics
Technological	ML module, SHAP explanations, dashboard, notifications via email/messenger	Signals are delivered to management automatically
Organizational	Risk committee, accountability matrix, escalation procedure	A clear owner and deadline for each signal
Personnel	Data literacy training for financial analysts	Model interpretation and trust
Information security	Data access control, confidentiality, and personal data protection requirements	Legal compliance, reliability

Implementation is carried out step by step. Each phase moves to the next only after its exit criterion is met, which makes it possible to manage costs and errors on the basis of pilot results.

Implementation in four phases, each closed by an exit criterion

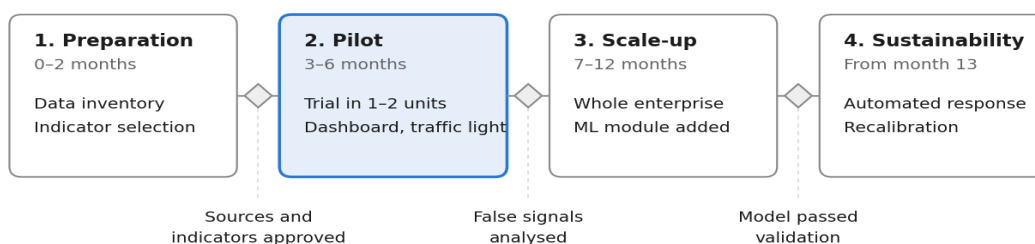


Figure 5. Roadmap for implementing the digital monitoring system

The main risks are low data quality, obsolescence of the model during operation (model risk), staff resistance, and implementation costs. To mitigate them, data quality indicators are monitored separately, the model is re-examined every quarter, and during the pilot, finance staff are involved as initiators of the project.

Conclusions and proposals

The research results indicate well-founded directions for improving digital monitoring and early warning systems in the management of enterprises' financial risks.

Conclusions:

1. Conventional monitoring based on annual or quarterly reports detects distress late; cash flow and receivables indicators deteriorate before balance sheet ratios.
2. A hybrid system combining classical models (Altman Z'), the multi-indicator IRI, and the ML-based probability of default (PD) extends the warning lead time and reduces false signals.
3. An effective system should have a five-layer architecture (sources, ETL, analytical core, alerting, decision-making) and a feedback mechanism.
4. In the illustrative simulation, the red signal was issued on average 5.5 months earlier than with conventional quarterly analysis; this result must be confirmed on real data.

PROPOSALS:

1. Create a single data warehouse for risk monitoring in enterprises and update the key indicators at least weekly.



2. Formalize the three-zone traffic-light system (green, yellow, red) with an escalation procedure that specifies a responsible person and an action deadline for each zone.
3. Calibrate the threshold values and IRI weights according to industry characteristics, and present ML model results in an interpretable form.
4. Start implementation with a pilot phase and control each phase through exit criteria.
5. Explore the possibilities for commercial banks to use this indicator system in the credit monitoring of client enterprises.

Future research may focus on backtesting the model on a sample of real enterprises, building separate models by industry, and adding supply chain and ESG risks to the indicator system.

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