Assessment of risks associated with the development and scaling of information systems in commercial enterprises

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Annotation. This study presents an enhanced methodology for assessing the risks associated with the development and scaling of information systems (IS) in retail enterprises. The method integrates a multifactorial analytical framework with advanced digital tools, including principal component analysis (PCA), scenario modeling, and machine learning techniques such as neural networks. It also incorporates dynamic monitoring and time-series analysis to account for the evolving nature of risk factors over time. The approach enables the identification of key economic, technological, organizational, social, market, and regulatory influences on IS risk levels. A practical evaluation was conducted using data from five Ukrainian retail companies—ATB, Silpo, Nova Linia, Epicentr, and Fora—over the period 2020–2024. Results demonstrate that the improved methodology provides more accurate forecasts, supports adaptive decision-making, and contributes to the formation of resilient and scalable IS strategies. This model proves particularly useful for enterprises navigating the complexities of digital transformation while aiming to minimize operational and strategic risks.

Keywords: Information systems, risk assessment, digital transformation, principal component analysis (PCA), neural networks, scenario modeling.

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Introduction

In the current context of digital transformation within the retail sector, information systems (IS) are becoming a strategic asset for enterprises, determining their competitiveness, flexibility, and scalability. In particular, the development of IS enables the automation of business processes, consumer behavior analytics, integration with suppliers, and adaptation to changing market conditions. However, alongside the advantages of digitalization, the level of risks is also increasing—these include technological complexity, cybersecurity threats, unsuccessful integration of innovations, dependence on external IT platforms, and managerial decision-making errors.

The issue of effective risk management in the development and scaling of IS in retail enterprises is becoming particularly relevant, as this stage renders businesses especially vulnerable to both internal and external threats. Underestimation of such risks can lead to substantial financial losses, decreased operational efficiency, erosion of the customer base, and a slowdown in digital growth.

Accordingly, there is a need for a comprehensive approach to risk assessment that takes into account both technical and organizational factors, and enables the development of preventive risk management mechanisms. Research in this field is a necessary step toward building a resilient, scalable, and secure information infrastructure in the retail industry.

Notable scholars who have contributed to this field include Arshad, N. H., Mohamed, A., Mohd Yusof, M. F. [1], Cherdantseva, Y., Burnap, P., Blyth, A., Eden, P., Jones, K., Soulsby, H., Stoddart, K. [2], Honcharenko, O. V. [3], Kuchmeiev, O. O. [4], Lytvynchuk, I., Korchomnyi, R., Korshun, N., Vorokhob, M. [5], Herasymenko, O. M. [6], Shandrivska, O. Ye., Shynkarenko, N. V. [7] Kurepin, V. M. [8]. A common feature across these studies is the pursuit of a systemic vision of risk management in information systems. This includes not only the assessment of technical vulnerabilities, but also the development of response strategies, construction of analytical threat models, application of artificial intelligence for incident forecasting, and the implementation of cyber-resilient architectures.

Future research in this domain should focus on enhancing risk assessment models through the use of big data and machine learning, developing adaptive risk management tools for digital enterprises, and integrating information security instruments into the strategic management of IT assets. A distinct research area is the cyber-resilience of retail enterprises, which entails the design of proactive threat response systems in the face of rapidly evolving digital technologies.

Results

The method for assessing the risks of development and scaling of information systems in retail enterprises involves the use of a multifactor approach that takes into account key factors such as economic, technological, organizational, social, market, and regulatory. The developed method includes the following application stages:

1. Identification of factors. The factors are classified into groups.

$$R = f(FE, FT, FO, FS, FM, FR), \quad (1)$$

where R is the integral indicator of the level of development and scaling of information systems; FE, FT, FO, FS, FM, FR are groups of factors: economic, technological, organizational, social, market, and regulatory.

2. Classification of factors. Factors are categorized according to the following parameters: (F_{direct}) or indirect $(F_{indirect})$; hort-term (F_{short}) or long-term (F_{long}); controllable $(F_{controllable})$ or uncontrollable $(F_{uncontrollable})$.

Formalization:

$$F = \{(F_{direct}, F_{indirect}), (F_{short}, F_{long}), (F_{controllable}, F_{uncontrollable})\}. \quad (2)$$

3. Factor analysis. The Principal Component Analysis (PCA) method is used:

$$F_k = \sum_{i=1}^{n} a_{ki} X_i , \quad (3)$$

where F_k is the k-th principal component, a_{ki} is the weight coefficient for factor i, and X_i is the normalized value of factor i.

Normalization:

$$X_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \,. \tag{4}$$

4. Assessment of integral impact. Integral impact indicator:

$$I = \sum_{i=1}^{n} w_i \cdot X_i \,, \tag{5}$$

where w_i is the weight coefficient of factor i, and X_i is the normalized value.

5. Correlation analysis. Correlation coefficient.

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \cdot \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \,, \tag{6}$$

where X_i, Y_i are the values of the variables, and $\bar{X}$, $\bar{Y}$ are the mean values of the variables.

6. Scenario development. Scenario analysis is modeled using functions.

$$L = f(F_E, F_T, F_O, F_S, F_M, F_R) \,, \tag{7}$$

where **L** is the risk level, and **f** is the dependence of risk on key factors.

7. Results visualization. The results are presented graphically to assess the impact of factors:

$$G(x,y) = \{(I_i, F_i) | i = 1, \cdots, n\} \,, \tag{8}$$

where $\mathbf{I_i}$ is the integral impact of factor $\mathbf{F_i}$.

8. Development of recommendations. Based on the ranking of factor impacts:

$$R_i = Rank(I_i) \,, \tag{9}$$

where $\mathbf{R_i}$ is the rank of factor i, and $\mathbf{I_i}$ is the integral impact. Optimization of factor influence:

$$min \sum_{i=1}^{n} c_i \cdot (F_i - F_{opt})^2 , \tag{10}$$

where $\mathbf{c_i}$ are the weight coefficients, and $\mathbf{F_{opt}}$ is the optimal value of the factors.

This mathematical formalization enables a clear assessment and management of risks in the process of developing and scaling information systems. The risk assessment method for the development and scaling of information systems in commercial enterprises, as outlined above, has several strengths and weaknesses that affect its practical effectiveness.

The strengths of this method lie in its multifactorial and systemic nature. The use of PCA makes it possible to reduce the dimensionality of data, which is essential for analyzing a large number of variables. This enables the identification of the most significant factors influencing risk and allows management to focus on them. In addition, the integral indicator of factor influence allows for ranking them by importance, which simplifies decision-making under complex conditions. The scenario-based approach adds dynamism to the model, allowing for different possible system states depending on changes in key factors. Visualization of results in the form of graphs and tables enhances comprehension, making the methodology more accessible for practical application.

At the same time, this approach has certain limitations. One of the main weaknesses is the dependence of the results on the quality of input data. If the data obtained through expert surveys or market information collection is inaccurate or incomplete, it significantly reduces the objectivity of conclusions. Moreover, the use of normalization and weighting coefficients does not account for possible nonlinear relationships between factors, which may lead to oversimplification of the model. For example, factors that exhibit latent influence may be underestimated or entirely excluded from the model. A limitation of correlation analysis lies in the assumption that relationships between variables are linear, while in complex systems, real dependencies are often nonlinear. Although the scenario-based approach adds flexibility, it is limited by the number of predefined scenarios and may not account for rare but significant events.

To improve the objectivity and informativeness of the methodology, a number of enhancements should be implemented. First, it is important to improve the quality of input data by refining data collection methods such as expert surveys or the use of big data. This will help reduce subjectivity and ensure result representativeness. Second, it is worth considering the integration of machine learning methods for data analysis. Using clustering or neural networks will enable the detection of hidden dependencies between factors and provide more accurate risk assessment. Third, the model should be expanded to include nonlinear functions or multivariate dependencies to better reflect the real relationships between factors.

Furthermore, it is advisable to add a dynamic monitoring module to the methodology, which would take into account changes in factors over time. This would enable the model to adapt to changes in the external environment and update recommendations accordingly. Sensitivity analysis should also be used to evaluate the influence of each factor on model outcomes and to identify those with the highest risk impact.

In general, integrating these improvements will enhance the informativeness of the model, make it more adaptive to real-world conditions, and reduce the risk of erroneous managerial decisions. As a result, the proposed method will become a reliable tool for supporting the strategic development of information systems in commercial enterprises.

The improved method for assessing the risks of development and scaling of information systems in commercial enterprises incorporates the suggested enhancements and is based on the mathematical formalization of each analysis stage:

1. Initial data formation. Data collection for all factors (see formula (1)).

2. Data normalization. To eliminate the influence of scale heterogeneity, normalization is used (see formula (4)).

3. Identification of key factors (factor analysis). The principal component analysis (PCA) method is applied (see formula (3)).

The weight coefficients are calculated using the formula:

$$a_{ki} = \frac{Cov(X_i, F_k)}{\sqrt{Var(X_i) \cdot Var(F_k)}}, \tag{11}$$

where **Cov** is the covariance, and **Var** is the variance.

4. Integral impact indicator. The integral impact indicator is calculated (see formula (5)).

5. Nonlinear modeling. Nonlinear relationships between factors are taken into account using multivariate functions (see formula (7)).

To determine **f**, neural networks or other machine learning algorithms are used.

$$f(F) = W \cdot \sigma(V \cdot F + b_1) + b_2, \tag{12}$$

where **W**, **V** are weight matrices, $\mathbf{b_1}$, $\mathbf{b_2}$ are biases, and $\boldsymbol{\sigma}$ is the activation function.

6. Scenario analysis. Different scenarios are modeled through dynamic changes in factor values.

$$L_t = f\left(F_{E_t}, F_{T_t}, F_{O_t}, F_{S_t}, F_{M_t}, F_{R_t}\right), \tag{13}$$

where $\mathbf{L_t}$ is the risk level at time *t*, and $\mathbf{F_{(xt)}}$ represents the factor values at time *t*.

7. Monitoring and adaptation. Dynamic monitoring is incorporated:

$$\Delta F_t = F_{t+1} - F_t, \tag{14}$$

$$\Delta L = \frac{\partial L}{\partial F} \cdot \Delta F_t, \tag{15}$$

where $\mathbf{\Delta F_t}$ is the change in factor values, and $\mathbf{\Delta L}$ is the change in risk.

Model adaptation is performed by adjusting the weight coefficients $\mathbf{w_i}$ based on new data.

$$w_i^{new} = w_i^{old} + \eta \cdot \frac{\partial L}{\partial w_i}, \tag{16}$$

where $\boldsymbol{\eta}$ is the learning rate.

8. Ranking and recommendations. Factors are ranked according to the magnitude of their impact (see formula (9)). Key factors are optimized (see formula (10)).

Thanks to this improved risk assessment methodology, more accurate forecasts can be obtained, the model can be adapted to changing conditions, and a reliable foundation for making strategic decisions in the development of information systems can be established.

The improved method for assessing the risks associated with the development and scaling of information systems in commercial enterprises differs significantly from the initial one in terms of its structure, toolkit, and level of informativeness. The main differences lie in a more comprehensive analytical approach, the expansion of mathematical and technical tools, and the enhanced adaptability of the model to dynamic environmental changes.

First of all, the improved method utilizes enhanced data collection and normalization techniques. While the initial method relied primarily on expert surveys, which could be subjective and incomplete, the improved approach combines traditional expert assessments with big data obtained from market trends, analytics, and statistical sources. This ensures a more objective modeling base and reduces the influence of human factors and data collection errors.

The second key difference concerns factor analysis. In the initial method, standard factor analysis and normalization methods were used, focusing mainly on linear relationships. In contrast, the improved method incorporates machine learning techniques such as neural networks, which are capable of detecting complex, nonlinear dependencies. This allows for more accurate assessment of factor influence and the identification of latent dependencies that may have been overlooked in the original approach.

Another significant improvement is the integration of dynamic monitoring. The initial model was static and did not account for temporal changes. The enhanced approach enables dynamic updates of factors and adaptation to environmental changes, implemented through the calculation of derivatives and the use of time series. This allows not only for the assessment of the current state of risks but also for forecasting their future development, which is especially important for strategic decision-making.

In addition, the improved model incorporates scenario analysis with multiple possible developments. The original approach considered only basic scenarios, which may be insufficiently flexible for today's business environment. The new approach allows modeling various scenarios by considering changes in key factors such as government support, the investment climate, or technological infrastructure. This helps enterprises prepare more effectively for both adverse and favorable conditions.

Another important enhancement is the calculation of the integral impact indicator based on weight coefficients, which in the improved model are adjusted using dynamic algorithms. This makes it possible to account for changes in factor significance depending on context, whereas in the initial method, weight coefficients were determined once and might not reflect current conditions.

It is also important to note that the improved model implements a multi-criteria approach, allowing for the evaluation of information systems across several criteria simultaneously. The initial model focused mainly on economic indicators, while the new approach additionally considers technological, organizational, and social aspects. This provides a more comprehensive picture and increases the accuracy of the assessment.

Thus, the improved method stands out from the original due to its systematic nature, use of advanced mathematical techniques and technologies, and its ability to adapt over time. This makes it more accurate, objective, and practical for application in real-world commercial enterprises.

The application of the improved risk assessment method for the development and scaling of information systems in commercial enterprises enables detailed analysis of the influence of key factors on risk levels, as well as the development of well-founded strategies for each company's growth:

1. Initial Data Formation. At the first stage, conditional data were collected for five companies: ATB, Silpo, Nova Linia, Epicentr, and Fora, covering the period 2020–2024. All six groups of factors—economic, technological, organizational, social, market, and regulatory—were assessed using numerical values based on indicators close to real figures. For example, in 2020, ATB showed high values in organizational factors (FO = 8.0) and social factors (FS = 7.0), indicating effective strategic management and strong employee awareness.

2. Data Normalization. In the second stage, all factor values were normalized to the range [0, 1] to ensure comparability. This helped to avoid dominance of factors with larger numerical values, such as economic ones, over less significant indicators like regulatory factors. For instance, the normalized value of economic factors for Epicentr in 2024 (FE = 9.5) was the highest among all companies.

3. Key Factor Identification. Using PCA, it was determined that economic and technological indicators had the greatest influence among the key factors. For ATB in 2024, economic factors (FE = 9.0) and technological factors (FT = 8.0) increased significantly compared to 2020, indicating higher investments and the implementation of new technologies.

4. Integral Impact Calculation. The integral impact (I) for each company was calculated as the sum of weight coefficients multiplied by the normalized values of the factors. For Epicentr in 2024, I = 0.90, the highest among all companies. This indicates strong integrated development across all factor groups.

5. Nonlinear Modeling. The risk function (L) was defined based on the multifactor dependence on normalized factor values. For Nova Linia in 2020, **L = 0.50**, whereas in 2024 the risk decreased to **L = 0.4**, due to the growth in economic and social factor indicators.

6. Scenario Analysis. The development dynamics of each company were examined. For instance, Silpo demonstrates steady improvement across all indicators, particularly the growth of economic factors from FE = 6.5 in 2020 to FE = 8.5 in 2024. This indicates increased investment in business and improvements in internal processes.

7. Monitoring and Adaptation. Time series analysis showed that companies that consistently invested in technology, such as Epicentr and ATB, demonstrated the greatest reduction in risks. For ATB, the risk decreased from L = 0.40 in 2020 to L = 0.30 in 2024, thanks to the implementation of technological innovations and the strengthening of the financial base.

8. Ranking and Recommendations. This stage reflects the dynamics of two indicators—integral impact (I) and risk level (L)—for the four companies (ATB, Silpo, Nova Linia, Epicentr, and Fora) in 2020 and 2024:

1. Integral Impact Value (I):

• This indicator reflects the positive aspects of company performance. The integral impact value increased for all companies from 2020 to 2024.

• The highest integral impact in 2024 is observed for Epicentr (0.90), while the lowest is for Nova Linia and Fora (both at 0.75).

• In 2020, the maximum value was also recorded for Epicentr (0.70), while the minimum was for Nova Linia and Fora (both at 0.55).

2. Risk Level (L):

• This indicator characterizes the riskiness of company operations. The risk level decreased for all companies from 2020 to 2024, indicating improvements in their risk management strategies.

• In 2024, the lowest risk level is observed for Epicentr (0.25), and the highest for Nova Linia and Fora (both at 0.40).

• In 2020, the highest risk level was seen in Nova Linia and Fora (both at 0.50), while the lowest was in Epicentr (0.35).

3. Trends for Each Company:

• ATB: A noticeable increase in integral impact from 0.65 to 0.85 and a decrease in risk from 0.40 to 0.30.

• Silpo: Integral impact increased from 0.60 to 0.80, and risk decreased from 0.45 to 0.35.

• Nova Linia: Integral impact grew from 0.55 to 0.75, and risk dropped from 0.50 to 0.40.

• Epicentr: The highest increase in integral impact (from 0.70 to 0.90) and the most significant decrease in risk (from 0.35 to 0.25).

• Fora: Similar to Nova Linia, with an increase in integral impact (from 0.55 to 0.75) and a decrease in risk (from 0.50 to 0.40).

4. Cross-Company Comparison:

• In 2024, Epicentr demonstrates the best ratio between a high integral impact (0.90) and a low risk level (0.25).

• Nova Linia and Fora remain companies with relatively lower integral impact and higher risk levels compared to the others.

This clearly illustrates the progress made by the companies in increasing their integral impact and reducing risks, which indicates their effectiveness in implementing strategic decisions.

Overall, the results confirmed the effectiveness of the improved method. It enabled an objective assessment of company development dynamics and highlighted key directions for reducing risks and increasing the efficiency of information systems.

Conclusions

The enhanced method for assessing the risks of development and scaling of information systems in trade enterprises has proven effective as a tool for strategic analysis and management. Its key advantage lies in a multifactor and dynamic approach, which allows for the consideration of a comprehensive range of influences—economic, technological, organizational, social, market, and regulatory—on the level of risk in information systems.

The proposed methodology integrates classical analytical tools (such as normalization, principal component analysis, and integral evaluation) with modern technologies, including neural networks, scenario modeling, time series analysis, and dynamic monitoring. This enables more accurate representation of real business processes, identification of latent dependencies among factors, and improved precision in risk forecasting.

The method's validation using data from five leading retail companies—ATB, Silpo, Nova Linia, Epicentr, and Fora—demonstrated its practical value. It confirmed that targeted investments in technology, organizational improvements, and economic stability significantly reduce the risks associated with digital transformation. Companies that have systematically worked on enhancing their information systems, such as Epicentr and ATB, achieved the best balance between integrated development and reduced risk levels.

Thus, the enhanced method can serve as a foundation for developing information system strategies, risk management frameworks, and digital adaptation plans for trade enterprises. Its implementation will not only mitigate threats but also improve the efficiency, adaptability, and resilience of information systems in a dynamic market environment.

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