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Digital solutions for risk management in sustainable development conditions of business ecosystems

Abstract

The article's objective is to conduct theoretical research of modern digital solutions for risk management in business ecosystems and develop an intelligent digital tool for risk management under sustainable development conditions. A comprehensive analysis of modern technologies that include artificial intelligence, big data, and blockchain, is conducted, their role in improving risk management efficiency is determined. The research methodology combines both theoretical methods (systems analysis, comparative analysis, SWOT analysis) and empirical methods (statistical analysis, machine learning methods, and experimental research). The main categories of risks are systematized, and possibilities for their optimization through digital solutions are explored. The impact of digital technologies on achieving sustainable development goals is analyzed, particularly in aspects of efficient resource usage, social integration, and innovation development. Key challenges of digital transformation in risk management are identified, including cybersecurity issues and regulatory requirements compliance. The practical application of machine learning methods for predicting employee attrition is examined, demonstrating the potential of digital solutions in solving specific business challenges. A prediction system that uses various machine learning algorithms was developed and tested. A comparative analysis of the effectiveness of various machine learning algorithms for the prediction task was conducted. When selecting the optimal classifier, both standard quality metrics and probability distribution analysis for identifying risk groups were taken into account. A modular system structure is proposed, and practical recommendations for implementing digital solutions in business ecosystems are provided.

1. INTRODUCTION

In a world where businesses face increasingly complex challenges such as climate change, regulatory changes, societal expectations for sustainable development, and market globalization, effective risk management is becoming a key factor in ensuring business stability and success.

Digital solutions, including the use of artificial intelligence, machine learning, big data, and blockchain technologies, offer opportunities to significantly improve risk management by increasing predictive accuracy, risk response efficiency, and resource optimization. However, digitalization also brings new risks, such as cybersecurity, technology failures and data loss. In this context, the integration of digital risk management solutions becomes an integral part of ensuring the sustainable development of business ecosystems, helping companies not only to survive but also to thrive in conditions of uncertainty. Moreover, sustainable risk management in business ecosystems allows maintaining a balance between economic, environmental and social factors, contributing not only to short-term efficiency, but also to long-term success, reducing negative impacts on the environment and society.

The objective of the paper is to conduct theoretical research of modern digital solutions for risk management in business ecosystems and to develop an intelligent digital tool for risk management under sustainable development conditions. To achieve this goal, the following tasks will be addressed:

- Analysis of the contribution of innovative digital solutions (artificial intelligence, big data, blockchain) to the efficiency of risk management in business ecosystems;
- Examine the main types of risks and assess the capabilities of digital solutions to minimize and prevent them;
- Analyzing practical implementation cases of digital solutions in various industries and their impact on business sustainability;
- Develop and validate an intelligent digital solution for risk prediction and management based on machine learning methods;
- Assess the challenges of implementing digital solutions, including cybersecurity issues, costs, and regulatory compliance requirements.

2. LITERATURE REVIEW

Digital risk management solutions and their impact on the sustainable development of business ecosystems have been extensively discussed in the academic literature.

Since Moore's (1993) introduction of the business ecosystem concept, it has attracted considerable scholarly attention. Iansiti & Levien (2004) further developed the theory by defining ecosystems as networks of interconnected organizations that create value through interaction. Peltoniemi (2006) further developed the concept by describing business ecosystems as dynamic structures in which organizations adapt through competition and cooperation. Adner (2006) contributed by outlining two basic approaches to ecosystems - structural and affiliative, while Gawer (2014) focused on platform-based ecosystems and their network effects. Jacobides et al. (2018) systematized these approaches by identifying three different types: business, innovation, and platform ecosystems. More recently, Nayak et al. (2022) extended this understanding by emphasizing ecosystems as metaphors for complex collaborative relationships between business organizations.

Traditional enterprise risk management includes identification, assessment, and management. Mitchell's (1995) definition of risk as a combination of the probability of loss and its impact remains fundamental to the field. Building on this, Dorfman (1997) identified four core risk management strategies: reduction, transfer/sharing, avoidance, and retention. However, business ecosystems change this traditional approach through the inherent interdependence of participants. Adner (2017) emphasized that participation in a business ecosystem creates unique risks associated with reliance on other participants to achieve success, which he categorized into three types: interdependence, integration, and initiative risks.

A significant contribution to the understanding of business ecosystem risks comes from the work of Smith (2013), who explored a systematic approach to risk identification and management when entering and participating in business ecosystems. His key contribution lies in proposing a two-stage risk management framework: preliminary assessment prior to ecosystem entry, and ongoing threat monitoring during participation. This approach enables organizations to develop more effective strategies within business ecosystems. Zamlynskyi et al. (2023) highlight the complex nature of modern risks, which affect all ecosystem participants and require integrated approaches to risk identification and management. Their research highlights digital risk and cybersecurity as critical factors for ecosystem sustainability, while also emphasizing the role of environmental, social, and governance (ESG) standards in ensuring ecosystem competitiveness and sustainable development.

The evolution of business ecosystems has increased the importance of digital solutions in risk management. Basic frameworks were developed by Figay et al. (2012) for ecosystem interoperability and Korpela et al. (2016) for digital integration. Senyo et al. (2019) further documented the growing demand for such solutions. The scientific literature review identified four key digital technologies that enhance ecosystem risk management and sustainability: artificial intelligence (AI), big data, blockchain, and financial technologies (fintech).

The application of artificial intelligence and machine learning in risk management has been extensively analyzed in the research literature. Studies by Brynjolfsson and McAfee (2014) and Davenport and Ronanki (2018) show how AI algorithms enhance the accuracy of risk prediction and automation in business ecosystems, contributing to their sustainability and adaptability through improved forecasting and decision making based on big data analysis. The study by Liu (2024) proposes a comprehensive approach to financial risk management using machine learning methods, especially for accurate measurement of risk, return, and portfolio exposure. The author emphasizes that increasing complexity has rendered statistical and simulation tools ineffective, necessitating the use of machine learning. Building on this understanding, Singh et al. (2024) propose an intelligent and distributed approach to financial fraud detection using big data technologies.

Another important aspect of risk management in business ecosystems is focused on blockchain and financial technologies. A foundational study by Tapscott and Tapscott (2016) established the role of blockchain in enhancing transparency and reducing supply chain risk. This concept was further developed by Allen et al. (2018), who analyzed blockchain as an institutional technology that transforms traditional trust mechanisms. Empirical evidence from Geng (2022) shows how fintech development strengthens the sustainability of the ecosystem by reducing information asymmetry and increasing innovation investment. Additional insights into fintech's potential for risk management in the financial sector are provided by Kabulova and Stankevičienė (2020) and Zhang and Lai (2022).

Ukrainian researchers are also actively engaged in this topic. For example, the research of Pizhuk (2021) analyzes the risks that arise during the process of digital transformation of Ukrainian business ecosystems and proposes solutions for the integration of digital technologies to improve the resilience of these ecosystems, with a particular focus on financial, operational, and environmental risks in the domestic context. The implementation of blockchain and cryptocurrency in the Ukrainian economy was studied by Greshko and Kharabara (20-23), with special attention to investment markets and financial risk management for strengthening the national economy. Domashenko et al. (2023) demonstrate the practical implementation of blockchain in financial-industrial ecosystems, focusing on digital cyber protection and integrated capital systems. Bondarenko et al. (2022) emphasize that fintech solutions allow not only to optimize financial risk management, but also to support sustainable development of business ecosystems through integration of modern digital solutions.

The analysis of the use of digital technologies for risk management in human resource management deserves attention. Studies by Bouhsaien and Azmani (2024), Vrontis et al. (2021), Fernandes França et al. (2023), and Palos-Sánchez et al. (2022) focus on the possibilities of implementing artificial intelligence in HR processes, including recruitment automation and HR function transformation. Woods et al. (2019) investigate the effectiveness of machine learning algorithms in predicting employee behavior, while Dennis and Aizenberg (2022) emphasize ethical aspects of AI application in HR management. Ukrainian researchers also contribute to this field: Kravchuk et al. (2024) study the transparency of decision-making in AI-driven HR processes, while Chernenko (2022) focuses on practical implementation aspects and associated risks.

Based on the existing research, it can be stated that the scientific potential of digital solutions for risk management in sustainable development conditions lies in the need for further analysis of the impact of digital technologies on the effectiveness of risk management, especially in the areas of financial risks, cybersecurity, and environmental sustainability. It is also important to study regulatory strategies that would ensure effective implementation of these solutions in the business ecosystems of Ukraine and the world.

3. METHODS

The research methodology is based on a combined approach that includes both theoretical and empirical methods, which is due to the two-component structure of the study: theoretical research of modern digital solutions for risk management and development of an intelligent prediction tool.

The theoretical part of the research is based on a systematic approach to the analysis of scientific literature and includes the following methods:

1. Systems analysis - for comprehensive study of digital solutions as a complex system of interconnected elements in the context of sustainable development of business ecosystems. This method allowed to identify structural connections between different components of digital solutions and their impact on the effectiveness of risk management.
2. Comparative analysis - to compare different approaches to implementing digital solutions, revealing their advantages and disadvantages in the context of risk management. The method was used to compare the effectiveness of different technologies (artificial intelligence, blockchain, big data) in solving risk management tasks.

The empirical part of the research, aimed at developing a turnover prediction system, includes the following methods:

1. Statistical Analysis - for processing and interpreting employee data, including demographic characteristics, performance indicators, and career development history. This method was chosen for its ability to identify patterns in large data sets.
2. Machine learning methods - to develop predictive models based on classification algorithms. These methods were chosen for their ability to identify complex non-linear relationships in the data and to provide high predictive accuracy. The selection of specific algorithms was based on several criteria: ability to handle categorical variables typical of HR data, resistance to overfitting, ability to assess feature importance, and ability to capture complex patterns in the data.
3. Experimental research - to validate the developed prediction system. The method includes:
- Cross-validation to assess model quality;
- Probability distribution analysis to identify risk groups;
- Comparative analysis of the effectiveness of different classification algorithms;
- SWOT analysis of the developed system to assess its strengths, weaknesses, opportunities and threats of implementation.

The system was implemented in Python using specialized machine learning libraries (scikit-learn, LightGBM, CatBoost). Python was chosen because of its extensive libraries and tools for data analysis and machine learning, its robust data visualization capabilities, and its potential for seamless integration with other systems.

This comprehensive approach to research methodology enabled a thorough study of the problem and the development of a practical solution for managing employee turnover risk in the context of sustainable development of business ecosystems.

4. RESULTS AND DISCUSSION

4.1. The role of digital solutions in achieving the SDGs

Digital solutions play a key role in achieving the Sustainable Development Goals (SDGs) defined by the United Nations. They facilitate the integration of innovative technologies into various economic sectors, increasing the efficiency, transparency and sustainability of business ecosystems. The main ways in which digital solutions contribute to achieving sustainable development goals include:

1. Use resources efficiently and reduce environmental impact:
- The Internet of Things (IoT) makes it possible to monitor and optimize the consumption of resources such as energy and water, reducing their inefficient use. For example, smart sensors can track energy consumption in real time, helping companies reduce greenhouse gas emissions;
- Artificial intelligence (AI) and big data are being used to predict climate change and develop strategies to reduce negative human impacts on the environment. These tools promote sustainable practices in agriculture, forestry, and natural resource management.
2. Social inclusion and reduction of inequalities:
- Mobile financial technologies (fintech) expand access to financial services for populations in underdeveloped regions. Microfinance and mobile payments based on digital platforms contribute to poverty alleviation and financial inclusion of low-income populations;
- Digital education through online courses and platforms provides access to knowledge and skills for people around the world, including those previously excluded from the educational process. This helps reduce inequality in access to education and creates new employment opportunities.
3. Encourage innovation and infrastructure development:
- Blockchain technologies provide transparency and security in supply chains, allowing each stage of production to be tracked. This reduces the risk of fraud and violations of environmental or social standards, and promotes sustainable business practices;
- Digital infrastructure (high-speed Internet networks, data centers) is the foundation for the development of new innovative solutions such as telemedicine, smart cities, and autonomous transportation systems. These technologies promote the sustainable development of urban areas and reduce environmental impact.
4. Business management and efficiency:

- The automation of business processes through AI, robotics and cloud solutions enables companies to increase efficiency, reduce costs and minimize environmental impact. This promotes the creation of green jobs and contributes to economic growth;
- Digital platforms promote transparency in government, especially in the public sector, helping to reduce corruption and increase the accountability of leaders. This ensures better control over resource allocation and sustainable project implementation.

5. Improve quality of life:

- "Smart cities use digital technologies to improve infrastructure, transportation, and energy systems to make cities more sustainable and livable. IoT sensors help to improve traffic management, reduce air pollution, and optimize the use of energy resources;
- Telemedicine and other digital healthcare solutions provide access to medical services in remote areas, improving the quality of life for people.

6. Effective risk management:

- Risk monitoring systems based on AI and big data enable early identification of risks related to environmental and social factors. This helps to better manage crises and prevent their negative impact on businesses and communities.

In this way, digital solutions open up new opportunities for achieving sustainable development goals, ensuring more efficient resource management, promoting social inclusion and stimulating economic growth. Innovative technologies not only help businesses adapt to today's challenges, but also contribute to preserving the environment and improving the quality of life for people.

4.2. Research gaps in digital solutions for risk management

Today's research on digital solutions for risk management reveals several significant gaps. A key problem is the lack of a comprehensive approach to the integration of digital technologies for risk management. Most works focus on analyzing individual technologies, such as artificial intelligence, blockchain, or big data, without considering their interactions and opportunities for comprehensive application. However, business ecosystems require integrated solutions that combine these tools to achieve maximum efficiency in risk management.

Another important gap is the lack of emphasis on the link between digital technologies and sustainable development goals. Although digital innovations are mainly discussed in the context of increasing economic efficiency, there is a lack of research that thoroughly analyzes their contribution to achieving specific sustainable development goals, such as responsible consumption and climate action (SDG 12 and SDG 13).

In addition, research often doesn't take into account the new types of risks that are emerging in the digital environment, in particular cyber risks, data breaches and technological failures. There is a tendency to focus on traditional financial and operational risks, while new digital threats continue to be underestimated.

Also, the specifics of risk management in regional contexts, especially in transition economies such as Ukraine, have not been sufficiently explored. Most works are oriented towards global or Western examples and do not take into account the specific challenges of local business ecosystems.

Finally, there is a lack of sufficient empirical research showing concrete examples of successful implementation of digital solutions in business ecosystems. Most of the existing work is theoretical in nature, creating a need for practical analysis.

4.3. Advanced digital solutions for risk management

Modern digital solutions for risk management offer companies the opportunity to respond more effectively to challenges using innovative technologies such as artificial intelligence, big data and blockchain. These tools make it possible to automate risk management processes, increase predictive accuracy, and reduce operational costs.

One of the most powerful tools in this area is Artificial Intelligence (AI) and Machine Learning (ML). They can perform predictive analytics by processing large amounts of data to identify potential risks. Using machine-learning algorithms, these technologies can detect anomalies in data that may indicate possible threats, such as cybercrime or financial violations. Platforms such as IBM Watson and Google Cloud AI are being used for risk analysis in a variety of industries, including financial markets, cybersecurity, and supply chain management. These solutions automatically process vast amounts of information, learn from data, and progressively improve their predictive accuracy, helping organizations respond to threats in a timely and accurate manner.

Another key technology is Big Data. By processing large volumes of structured and unstructured data in real time, companies can make more accurate predictions about potential risks. Big data analytics tools such as Splunk and Cloudera help organizations across industries analyze information about user behavior, financial operations, and external threats. These platforms can process data from multiple sources and provide analytical insights that enable organizations to make informed decisions to mitigate risk.

In addition, blockchain technologies play an important role in increasing transparency and reliability in risk management. Decentralized blockchain-based solutions, such as Ethereum and Hyperledger, make it possible to track transactions and supply chains with minimal opportunities for manipulation or fraud. This is particularly important for reducing risk in financial operations and logistics processes. Blockchain ensures data transparency and authenticity, which is critical for companies that work with large amounts of information and conduct international transactions.

Modern digital risk management solutions are based on innovative technologies that enable companies to increase their flexibility, accuracy, and resilience to external and internal threats. Artificial intelligence, big data, and blockchain significantly expand the ability to predict and minimize risk, giving companies a competitive edge in a rapidly changing environment.

4.4. Integrating digital solutions

One of the key aspects of integrating digital solutions is the ability of artificial intelligence and big data to analyze and optimize business processes in real time. For example, companies can use these technologies to manage resources more efficiently, reduce energy losses, cut costs, and reduce greenhouse gas emissions. This is particularly relevant in the industrial and transportation sectors, where the implementation of intelligent monitoring systems enables more sustainable use of natural resources and responsible consumption, in line with SDG 12 (responsible consumption and production).

Blockchain technologies also play an important role in creating transparent and trustworthy business ecosystems. Due to the decentralized nature of blockchain, companies can track each step in the supply chain and ensure operational transparency, which helps minimize the risk of fraud, non-compliance with ethical standards, or violations of environmental regulations. For example, in the manufacturing or agricultural sectors, blockchain enables transparency into the origin of goods and resources, verifying their compliance with environmental standards and sustainable development requirements.

The integration of these digital solutions into business ecosystems also improves collaboration between different market participants. Big data and AI can be used to predict changes in market conditions or consumer behavior, allowing companies to respond quickly to risks and adapt their strategies to meet the needs of sustainable development. Digital platforms for data exchange between businesses, governments and public organizations create an environment for collaboration that helps implement sustainable economic policies and social initiatives.

In the context of financial business ecosystems, digital financial technologies (fintech) play an important role in providing access to financial services for small and medium-sized enterprises (SMEs), which is crucial for economic growth and reducing inequality. The use of mobile payments, blockchain, and cryptocurrencies enables financial inclusion, especially in regions with limited access to traditional banking services. This not only contributes to economic stability, but also to social inclusion, which is an essential component of sustainable development (SDGs 1, 10).

In this way, digital solutions not only improve risk management in business ecosystems, but also support sustainable development strategies, helping companies achieve a balance between economic results, social goals and environmental responsibility. The integration of these technologies creates the conditions for the development of resilient and adaptive business ecosystems, capable not only of responding to today's challenges, but also of promoting long-term development in harmony with nature and society.

4.5. Results of the development of an employee turnover risk prediction system

In the context of risk management in business ecosystems, employee turnover is a critical issue that directly affects business stability and efficiency. The analysis of HR systems available on the Ukrainian market shows that most of the available solutions focus primarily on the optimization of recruitment processes, onboarding new employees, and talent identification.

Given the potential of AI technologies and machine learning to analyze large employee data sets, the development of specialized systems for predicting attrition risk is becoming an important direction in the development of digital solutions in human resources management.

The study developed and tested an employee turnover risk prediction system based on machine learning methods, which enables the early detection of potential risks. The experimental part of the study was based on a publicly available dataset containing employee information, including demographic characteristics, performance indicators, career development data, and turnover status. The prediction system was implemented in Python using specialized machine learning libraries.

Turnover prediction is a supervised binary classification task. The choice of algorithm for such tasks depends on many factors, and it's important to understand that no single method is universally the best, and often the optimal solution is a combination of different approaches. Various classification approaches have been tested, from simple algorithms to more complex ensemble methods (Fig. 1), which allowed to evaluate their effectiveness in solving the given task and to choose the optimal solution considering the domain specifics.

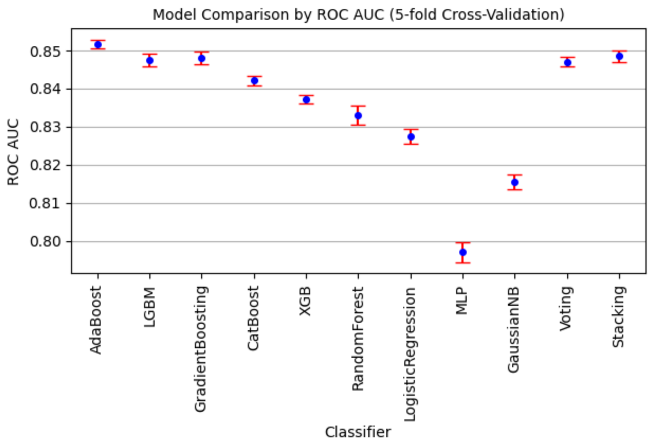
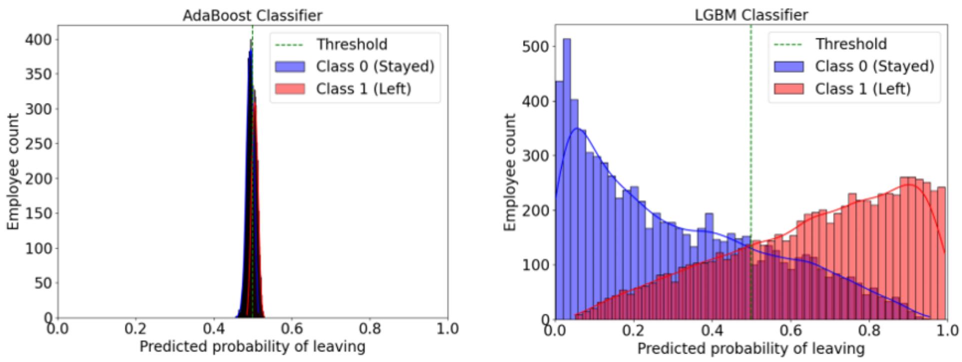


Fig. 1. Comparison of classifier performance using ROC AUC scores obtained through 5-fold cross-validation

In selecting the optimal classifier, attention was paid not only to standard quality metrics, but also to probability distribution analysis. This approach revealed that some classifiers, despite having high accuracy metrics, proved to be unsuitable for practical use in risk group identification. For example, the AdaBoost classifier, despite having high quality metrics, has too "sharp" a probability distribution, making it difficult to identify employees with increased turnover risk (Figure 2, a). In contrast, other ensemble methods showed a more balanced probability distribution, similar to that shown in the graph for the LGBM classifier (Fig. 2, b). Such a distribution is more meaningful for practical applications, as it allows for more accurate grading of risk levels and identification of employees who require more attention from HR.



(a) AdaBoost predictions **(b)** LGBM predictions

Fig. 2. Distribution of predicted probabilities

Feature selection plays a crucial role in HR analytics and retention management, as it helps to identify key factors that influence employees' decisions to leave. To determine the optimal feature selection method, a comparative analysis of different approaches was conducted. The effectiveness of the methods was evaluated using a single classifier to ensure an objective comparison. Analysis of the results showed that Lasso and RFECV methods provide the highest performance, demonstrating not only high accuracy metrics, but also stable probability distribution across different classes.

Based on the research results, an employee turnover prediction system was developed whose structure includes interconnected components that ensure a complete cycle from data analysis to prediction generation (Fig. 3).

The Data Analysis module performs comprehensive analysis of input information, including exploratory data analysis, categorical feature coding mapping generation, multicollinearity elimination, and significant feature selection. This module provides data preparation for model training and subsequent prediction. The results of the module are stored in the data store as a preprocessing_settings structure, which contains all the necessary parameters for consistent data processing in the system.

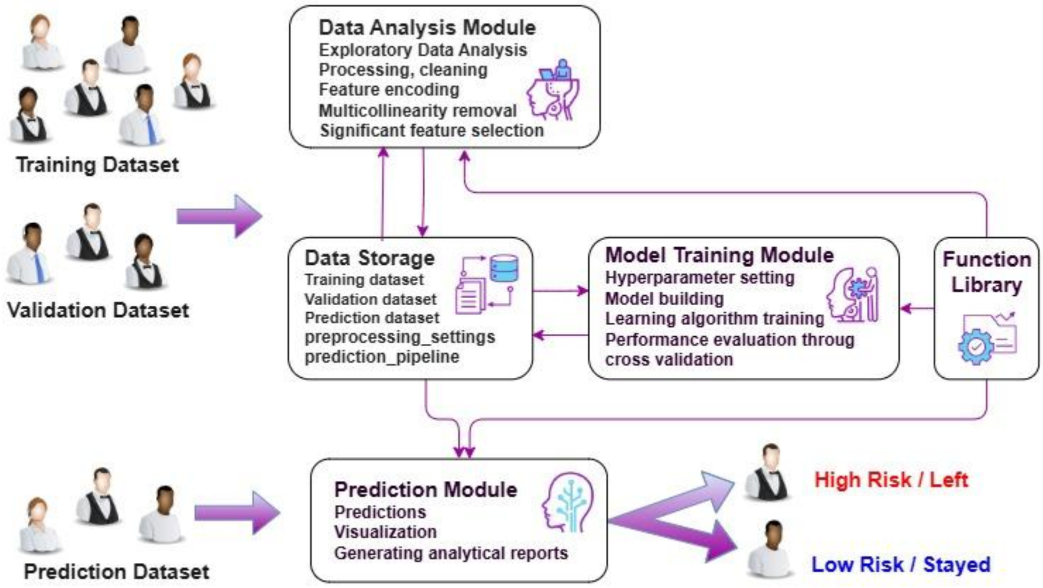


Fig. 3. Structure of the developed employee turnover prediction system

The Model Training module is responsible for building, training, and storing the predictive model. The module implements a model hyperparameter optimization mechanism that allows automatic configuration adjustment for specific data sets. The trained model, along with data transformation components (scaling and dimensionality reduction), is stored in the data store as a prediction_pipeline package. This ensures system stability and scalability, and also simplifies the use of the model in other modules.

The prediction module is responsible for making predictions and generating analytical reports based on processed employee data. This module loads the prediction_pipeline package from the data store to sequentially apply transformations and the predictive model to the input data. The results of this module are visualized as reports and graphs for easy interpretation by HR professionals.

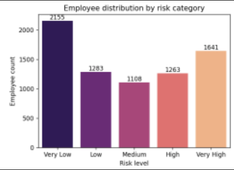
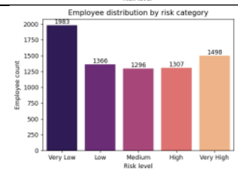
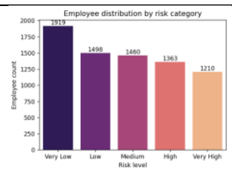
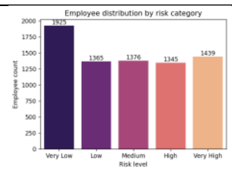
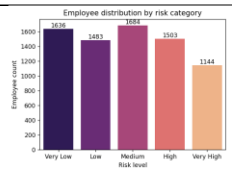
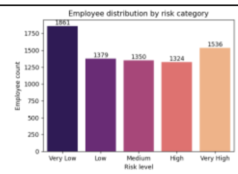
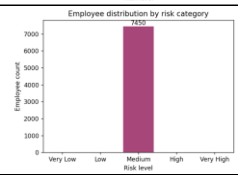
The function library provides system functionality, including tools for data preparation and processing, feature encoding, calculation of model performance metrics, and visualization of results. This module is universal and is used by other system modules at various stages of operation. This approach ensures standardization of data processing and reduces code duplication.

Coordinated interaction between modules is provided by the data store, which stores: training data for model building; test data for accuracy evaluation; preprocessing_settings - structure containing data preprocessing and feature selection settings; prediction_pipeline - package containing the trained model and all data transformation components. Data storage allows other modules to work with consistent data, ensuring process standardization at all stages.

An important advantage of the system is its flexibility in selecting and testing different machine learning methods. The modular structure of the system allows easy replacement of classification algorithms by modifying the corresponding module without affecting other parts of the system. This provides the ability to experiment with different prediction approaches, from simple linear models to complex ensemble methods, choosing the optimal algorithm for specific conditions.

When choosing an optimal classifier, it is important to consider not only the prediction accuracy, but also the computational efficiency of the model. A comparative analysis of the training and optimization time characteristics of different classifiers (Table 1) revealed significant differences in their computational efficiency.

Tab. 1. Testing results of the prediction system with different classifiers

Classifier	**ROC AUC**	**Recall**	**Optimization time (sec)**	**Training time (sec)**	**Probability distribution by risk groups**
Stacking Classifier	0,8451	0,7395	2613,8545	305,6151	
Gradient Boost Classifier	0,8458	0,7401	852,1347	11,1144	
CatBoost Classifier	0,8460	0,7137	1054,6521	3,3504	
LGBM Classifier	0,8452	0,7420	217,0202	1,2232	
Random Forest Classifier	0,8381	0,7332	561,6284	44,1696	
MLP Classifier	0,8400	0,7065	2916,1577	75,2652	
AdaBoost Classifier	0,8469	0,7382	584,0277	20,7820	

The MLP and Stacking classifiers required the most time for optimization, while the LGBM classifier proved to be the most efficient in terms of processing speed. It is important to note that for the Stacking Classifier, while hyperparameter optimization led to a significant increase in computation time, it did not lead to a significant improvement in prediction quality. This indicates that the base configuration of the model already provides an optimal balance between prediction efficiency and computational cost.

The system is dynamic due to the ability to update the training data set. As new information about employee turnover becomes available, this data can be incorporated into the training set, allowing the model to be periodically retrained. Such adaptivity ensures that predictions remain relevant even as employee characteristics or business environment conditions change. The preprocessing_settings structure and prediction_pipeline package support this dynamism by storing not only the model itself, but also data preprocessing parameters and feature selection settings, ensuring consistency during system updates.

The conducted SWOT analysis of the developed system revealed its strengths and outlined areas for improvement (Fig. 4). The research results demonstrated the high effectiveness of the developed system in predicting employee turnover. The identified key factors influencing turnover decisions can be used by HR departments to develop retention strategies, especially for employees at high risk of turnover.

STRENGTHS	WEAKNESSES
• Modular structure ensures flexibility, scalability and ease of modifications. • Centralized data storage guarantees consistency and process standardization. • Automation of model settings and training data updates ensures prediction relevance. • Intuitive result visualization simplifies analysis for HR specialists. • Versatility of function library.	• Dependence on data quality and completeness. • High technical infrastructure requirements. • Complexity of initial system setup. • Lack of automatic model performance monitoring.
OPPORTUNITIES	**THREATS**
• Integration with HR systems for automated data collection and analysis. • Implementation of new algorithms to improve prediction accuracy. • Functionality expansion to solve other HR tasks. • Automation of model performance monitoring and accuracy decline notifications.	• Risks of data leakage and non-compliance with privacy legislation. • Technical failures or changes in business environment may reduce model effectiveness. • Competition with commercial HR solutions. • Resistance from HR specialists due to distrust in automated system predictions.

Fig. 4. SWOT Analysis of the developed system

The system has a clear modular structure, high flexibility and scalability, which are its main advantages. However, to ensure its effective operation, it's important to consider the dependence on data quality and the need for technical support. Opportunities for functionality expansion and integration with other HR systems open up prospects for further development, while risks are associated with data security, technical failures, and regulatory constraints.

5. CONCLUSIONS

The research revealed that the integration of digital solutions for risk management in sustainable development conditions of business ecosystems is an important step toward increasing the resilience and adaptability of modern organizations. The implementation of innovative technologies, such as artificial intelligence, machine learning, big data, and blockchain, significantly improves risk prediction accuracy, facilitates prompt responses to external and internal threats and optimizes management processes in organizations across various industries.

The significance of digital solutions for risk management is particularly relevant in the context of sustainable development, as they not only increase the economic efficiency of enterprises, but also contribute to addressing social and environmental challenges. Thanks to the ability to predict risks and manage resources in real-time, digital solutions allow companies to reduce negative environmental impact, which is an important component of achieving sustainable development goals.

At the practical level, the use of machine learning methods for predicting employee turnover demonstrated high effectiveness. The prediction system based on analyzing large data sets and applying modern algorithms, showed significant advantages in prediction accuracy. This allows organizations to reduce costs for recruitment and training of new employees and develop retention strategies considering resignation risks.

The obtained results confirm the necessity of further development and adaptation of digital solutions to specific conditions of business ecosystems, particularly in countries with transition economies, such as

Ukraine. It is also important to consider risks that arise in the digital transformation process, particularly cyber risks and technological failures, and develop strategies for their minimization.

Overall, the implementation of digital technologies in risk management processes is strategically important for ensuring sustainable development of organizations and business ecosystems in modern conditions of global challenges and uncertainty.

Conflicts of Interest

The authors declare that there is no conflict of interest for this manuscript.

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