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RESEARCH ARTICLE

Developing a Model for Forecasting Risks of Innovative Entrepreneurial Projects with Machine Learning Tools

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ABSTRACT

The implementation of innovative entrepreneurial projects is essential for economic progress, as it leads to increased productivity through improved technology, new products, services, and markets and ultimately facilitates the economic growth of the country. There are positive trends in the government's development and support of business projects and entrepreneurial infrastructure, with various programs being implemented. At the same time, innovative entrepreneurial projects are pretty risky, as only some are breakeven and effective. The lack of data analysis of successful and unsuccessful innovative business projects exacerbates the situation. This study applies machine learning to predict risks by analysing historical data on closed projects. The authors examine a database of innovative entrepreneurial projects from a startup graveyard website. Based on publicly available data on the causes of project closure, a model was built and trained to predict risks such as inconsistency with market needs, competition, and failures in business model selection.

INTRODUCTION

Implementing innovative entrepreneurial projects is an essential process in economic activity. It leads to increased productivity through improved technology, better resource combinations, and the emergence of new products, services, and markets, ultimately facilitating economic growth (Zaytsev et al.,2021). The McKinsey Global Institute report for 2018 demonstrated the dependence between innovation and economic growth. The study proved that companies that invested in innovation development received higher profits. These companies helped increase GDP in 18 countries and contributed to the country's development (Woetzel et al., 2018; Bibi & Safia Shaukat, 2023).

Implementing innovative entrepreneurial projects is now supported and encouraged at the state level. The state can act as a facilitator of innovation, for example, in the case of solar panels and Tesla battery technologies, developed with grant support from the US Department of Energy. In Russia, such an innovation is the GLONASS navigation system, which was created for military purposes and became available to the public. The state acts as the founder of the innovation infrastructure. There are innovation centres in Russia, such as Skolkovo, the Russian Science Foundation (RSF), and the Innovation Promotion Foundation (IFI). The state also provides funding for the implementation of innovative entrepreneurial projects (Rodionov et al., 2022). Higher education institutions play an essential role in innovation, generating and commercializing knowledge at the country level and forming a national innovation system (Rodionov & Velichenkova, 2020; Terenteva et al., 2023).

The innovative triple helix model involves interaction between universities, industrial enterprises and the government, and the creation of hybrid organizations such as technology transfer centres at universities, enterprises, and research laboratories. Today, a university is an institution that reproduces and accumulates knowledge and attracts young minds and idea generators. Modern universities support the triple helix model, the other two elements of which are the state and business (Yu, 2022).

On December 15, 2021, the Russian government approved the Federal "University Technological Entrepreneurship Platform" project. The project's goal is to develop student technological entrepreneurship. To achieve this goal, several activities are planned, such as implementing the "Student Startup" grant competition to launch and support technology projects, creating entrepreneurial infrastructure on the campus, and launching acceleration programs.

Consequently, the state plays a significant role in developing entrepreneurship and innovation by implementing technology programs, supporting a mentoring system, and creating and assisting development institutions (Borisov et al., 2022).

However, the problem is that only a few innovative business projects survive and continue to develop. This is due to uncertainty and risks that are difficult to predict in the early stages of an innovation project. Another problem is the ineffective use of already implemented innovation projects to identify factors contributing to the success or failure of the project. The problem is that government and venture funds involved in financing innovative projects tend to pay more attention to new projects instead of analysing and understanding the reasons for the failure of closed ones. This leads to the ineffective implementation of quite a few innovative projects.

The study authors propose forecasting possible risks in the early stages of innovative entrepreneurial projects using machine learning tools and relying on information about closed projects. The advantages of using machine learning to forecast the risks of innovative projects are the following: automation of risk forecasting, high accuracy, the ability to collect data, and continuous improvement of the forecast model. Particular attention should be paid to universities that are centres of innovation and provide resources for implementing innovative entrepreneurial projects.

LITERATURE REVIEW

Knight et al.'s study illustrates how risk is frequently related to uncertainty, Whereas A.Kh. Willett explained that risk objectively correlates with subjective uncertainty (Kubar & Dadyka, 20164). F. Knight advocates not relying on intuition when assessing risks but instead assessing them systematically using various criteria and analysis of data and information. One of the essential criteria that Knight recommends when assessing risk is the likelihood of an undesirable event. Knight emphasizes the importance of assessing risk based on reliable data and information and recommends collecting and analyzing data on previous historical risk events (Raue & Scholl, 2018). A. Cadareja published a series of studies on risk assessment of innovative entrepreneurial projects. He classified risks as external and internal, as well as risks associated with different types of innovation—the main idea of A. Cadareja's work is that if an organization monitors and assesses risks throughout the entire life cycle of an innovative project, and this assessment is fixed at the level of the organization's culture, then the likelihood of success of innovative projects increases by more than 35% (Kadareja, 2013). In their work, Datta Sumit and S.K. Mukherjee argue that identification and forecasting of risks must be carried out in the early stages of the innovative project implementation, based on the historical experience of implemented projects, which makes it possible to identify potential problems and develop strategies for solving them.

To identify and assess risks early in the project, the authors suggest conducting risk seminars in parallel with preparing a business case for the project. Datta Sumit and S.K. Mukherjee also highlight the importance of quantitative assessment of risks and their aggregations, which allows prioritization of risk management and ensures effective risk management (Datta & Mukherjee, 2001). A review of scientific literature concluded that risk management is an integral means of achieving the success of an innovative project (Sergeeva & Nekrasova, 2017). The authors noted the need to forecast risks early in implementing a creative project and the importance of quantitative assessment to prioritize risks. However, the works presented emphasize the importance of predicting risks at the level of organizations' corporate culture without considering the interests of stakeholders such as the state, private, and venture investors. Haloul et al., (2024) emphasizes the importance of identifying and predicting risks for each stakeholder of an innovative project: the project team, investors, and the state

Machine learning makes it possible to predict risk based on the historical experience of implemented innovative entrepreneurial projects. Several studies in the scientific field are currently examining the use of machine learning to forecast the success of innovative entrepreneurial projects (Orlova Ekaterina, 2023).

A machine learning model to predict whether startups will go public or fail. The following algorithms were used to train the model: XGBoost, random forest, and K-nearest neighbours. The model trained with the random forest algorithm showed high accuracy - 89% (Ross et al., 2021). B. Sarlic and others used CatBoost and logistic regression algorithms to build a model that predicts whether a startup receiving seed or angel funding will reach Round A within the following year. The accuracy of the trained model was 85% (Sharchilev et al., 2018). Alfahad et al., (2022) developed a model that predicts the probability of receiving an investment with 88.9% accuracy. The random forest algorithm model was the most accurate (Krishna et al., 2016;). U. Kaiser and J. Kuhn's study used open-source qualitative and quantitative data to develop a model that predicts startup success. Data such as industry, profitability, quality characteristics of the manager, legal form, company name, and founder's name were considered to develop the model. Based on this data, scientists have developed two models that determine the profitability and survival of a company. The accuracy of the pre-trained models was 68% and 82%, respectively (Kaiser & Kuhn, 2020). The authors mentioned above have developed models predicting the success of innovative entrepreneurial projects. The most accurate results were obtained using the Random Forest algorithm, which will be used in further research.

This scientific research demonstrates the relevance of using machine learning methods to predict the success of startups. However, no studies were found that used machine learning to predict the likelihood of a specific risk in an innovative entrepreneurial project. This study examines a model that will predict the possibility of risks in innovative entrepreneurial projects. This risk probability forecasting model will become a tool for strategic planning, and machine learning methods will identify project bottlenecks and factors that led to an event that harmed the project.

The Study Objective and Tasks

The study's object is to innovative university projects. Its subject is using machine learning to forecast risks in implementing innovative projects. The study aims to develop a risk forecasting model for innovative entrepreneurial projects. To achieve the goal, the following tasks have been solved:

1. Collection of data on innovative entrepreneurial projects
2. Research into the reasons for the closure of innovative entrepreneurial projects
3. Data processing and formation of a training sample
4. Selection of machine learning algorithms for the model

5. Development of a machine learning model
6. Assessing the accuracy of the pre-trained model for predicting the risks of innovative entrepreneurial projects.

The work's theoretical significance lies in studying the specifics of using machine-learning methods to forecast risks in implementing innovative projects. Its practical relevance is due to the possibility of using the model developed by the authors to predict the risks of innovative entrepreneurial projects in business incubators and university accelerators.

RESEARCH METHOD

Many methods are presented in the ISO to solve the problems of assessing the risks of innovative business projects (IEC 31010:2019 standard "Risk Management. Risk assessment methods"). However, these methods require the involvement of experts and the direct participation of the project team. Moreover, these methods are based on subjective judgments. This study proposes using available historical data on projects that have been implemented. In this study, a classification problem is solved to forecast the risks of innovative entrepreneurial projects, where 1 is a high probability of a specific adverse event, and 0 means that the risk is unlikely. For this purpose, machine-learning algorithms will be used, and a model will be developed. Random Forests and Decision trees are used as model training methods (Dharmadasa, 2023).

The random forest method, proposed by L. Breiman and A. Cutler, uses a large ensemble of decision trees, each giving a low classification quality. However, the large number of trees makes their overall forecasting accuracy high. The basic principles of the random forest method are the following:

1. A random subsample of training data is used at each tree construction stage, allowing you to create various trees, helping avoid overtraining, and increasing the model's generalization ability.
2. A random set of features is selected When constructing each branch in the tree. This further contributes to trees' diversity and reduces their correlation (Biau & Scornet, 2016).

This method's advantages include high scalability and accuracy, resistance to outliers, processing data with many features and classes, and working with missing data. The decision tree acts as a structural element of a random forest. K. Shannon is the author of this method. A binary tree was used to forecast the risks of innovative entrepreneurial projects, with precisely two edges emerging from each node (Nasteski, 2017).

RESEARCH RESULTS

To determine risk factors, innovative entrepreneurial projects that have been closed were studied in the USA, Canada, Great Britain, Germany, Spain, France, Sweden, Estonia, Latvia, Australia, China, India, Japan and Indonesia. The data source is the startup graveyard on www.failory.com. The site's database contains more than 200 startups and company projects, which analyses the reasons for their failures. To compile the sample, 100 startups opened between 2009 and 2018 were examined (see Figure 1).

Figure 1. Years of the start of innovative entrepreneurial projects selected for further research (Nico, 2024, Failory database). During the study, the following risk factors led to project closures (see Table 1).

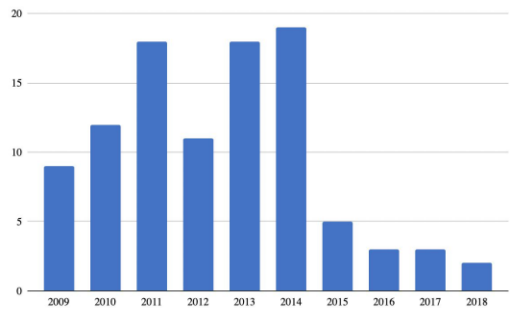

Figure 1. Years of the start of innovative entrepreneurial projects selected for further research (Nico, 2024)

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Table 1: Characteristics of risk factors for innovative entrepreneurial projects

Risk factor	**Characteristics**
1	2
Inconsistency with market needs	The product is not in the demand of its target audience.
Burnout	Incorrect distribution of tasks within the team and difficulties in introducing the project to the market due to the psychological inability of the project leader to continue product development
Legal problems	The product encountered resistance in the legal field (usually from the state)
Narrow segment	The product solves a consumer problem that is too narrow, which subsequently does not compensate for the company’s costs of maintaining the product
Competitors	Product is taken over by competitors or squeezed out of the market
Insufficient funding	The product has not received sufficient funding for development
Inconsistency between partners	Disagreements within the team hinder the development of a single business development strategy
Lack of specialists on the team	The existing team does not have the necessary functionality for the product or is too small to distribute tasks
Wrong marketing strategy	The wrong promotion methods were chosen to promote the product, or the project's founders underestimated this area.
Incorrect business model	The project founder incorrectly identified key activities, sales channels, consumer segments, or other essential components of the business model
Premature scaling	The product used enormous funding to expand without having the prerequisites for this in the market.

The most common risk factors were selected to create a machine-learning model. Figure 2 shows a diagram of the risk factors that led to the closure of innovative entrepreneurial projects.

The diagram analysis shows that the most common factors leading to the project's closure were inconsistency with market needs, failure to choose a proper business model, and competition. These risk factors totaled 63%.

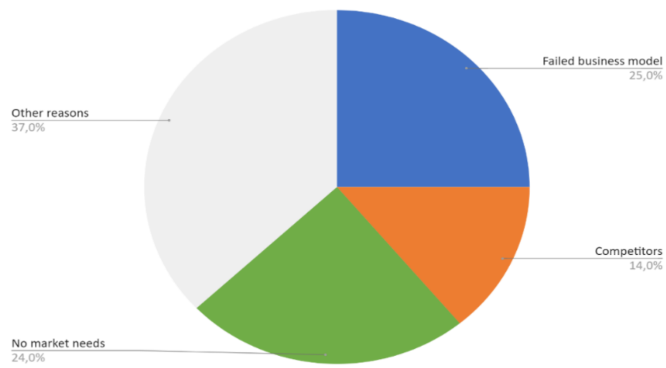

Figure 2 Frequency of occurrence of risk factors (Nico, 2024, Failory database)

Diagram 3 shows the relationship between the areas of innovation projects and the frequency of risk factors occurrence.

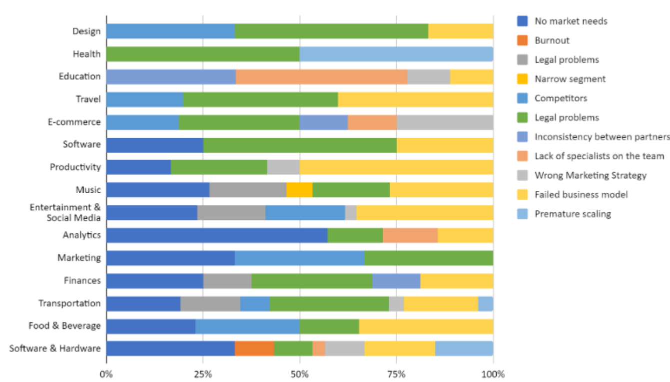

Figure 3 Correlation between the frequency of risk factors occurrence and the areas of innovative entrepreneurial projects (Nico, 2024, Failory database)

This diagram shows that more than four risk factors may occur in some areas. For example, competition risk prevails in high-tech industries. Legal restrictions are the leading risk factor in the financial sector. In some areas, more capital investment and resources are required for successful business development.

To develop a machine-learning model that can predict the likelihood of risk occurrence, it is necessary to identify the quantitative criteria based on which the model will make risk predictions. The model's response (target value) will be the occurrence of an unfavourable event associated with a particular risk, i.e. class 1 is characterized by a high probability of risk, and class 0 is characterized by a low likelihood of risk. Based on the available information, the following criteria will be used to train the model: area of activity, country, year of the project start, number of project founders, number of employees, amount of investment, round of investment, and duration of project activity. This study uses a sample with quantitative values of these criteria, which are prognostic indicators for assessing the likelihood of risk occurrence. These criteria are universal and apply to all risk factors. The limitations of the study are as follows:

1) A small database of innovative entrepreneurial projects for the 2015-2020 years of start

2) Limited information in the available sample. From the information available, we can select the following criteria: area of activity, country, number of founders, number of employees, amount of investment, round of investment, year of implementation start, and duration of the startup. At the same time, additional criteria are needed to predict the risk factors of innovative entrepreneurial projects, such as the qualitative characteristics of the startup founders, time spent on the project, etc.

Innovative entrepreneurial projects were classified as follows (see Tables 2 and 3) to determine the quantitative values of criteria such as the number of employees and the amount of investment.

Table 2 – Classification of projects according to the criterion "number of employees"

Number of employees	**Class**
1-10	1
10-50	2
50-100	3
more than 100	4

Table 3 – Classification of projects according to the criterion "amount of investment"

Investment size	**Class**
up to 1 million dollars	1
1 – 5 million dollars	2
5 – 15 million dollars	3
15 – 50 million dollars	4
50 – 150 million dollars	5
more than 150 million dollars	6

This classification made it possible to simplify data analysis and processing. The accuracy metric, calculated using formula 1, characterizes the accuracy of a trained model and reflects the proportion of correct answers (Lü et al., 2020).

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

TP is an actual positive class 1 determined by the model, TN is a valid negative class 0 determined by the model, FP is the model incorrectly predicted class 1, and FN is the model incorrectly predicted class 0. A machine-learning model was built and trained using the Microsoft Machine Learning Studio tool (see Figure 4).

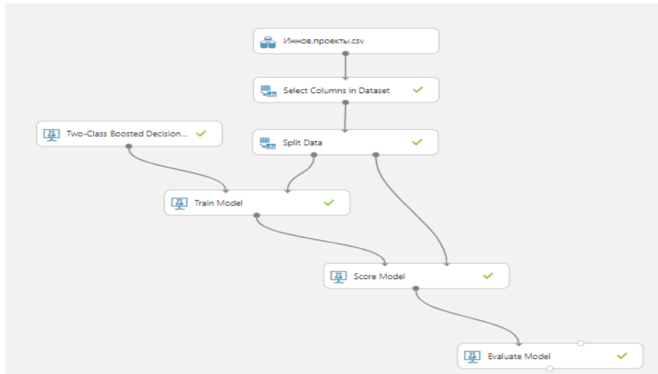

Figure 4 Machine learning model [compiled by the author]

The "Select Column Dataset" block limited the number of columns available for training; the sample with information about the project's name was excluded. Using the "Split Data" component, the sample containing quantitative values according to the criteria (see Table 1) was divided into training and testing in a 75/25 ratio. Next, the model was trained using the Random Forest method.

Figure 5 shows the decision tree for the risk factor "Inconsistency with market needs." Using the model, it was revealed that the "Area of activity" and "Number of employees" criteria most influence the likelihood of this risk factor. "Area of activity determines the project's target audience, and "Number of employees" affects the company's scale and capabilities.

Suppose an innovative entrepreneurial project is implemented in an industry with low demand for its product or service. In that case, this may lead to the risk factor of "Inconsistency with market needs". The "Number of employees" criterion is also significant in the risk occurrence. Suppose a startup has a small number of employees. In that case, this may limit its ability to develop and improve the product, which, in turn, may lead to risk factors such as "Inconsistency with market needs" or "Competition". The accuracy of forecasting the risk factor "Inconsistency with market needs" was 64%.

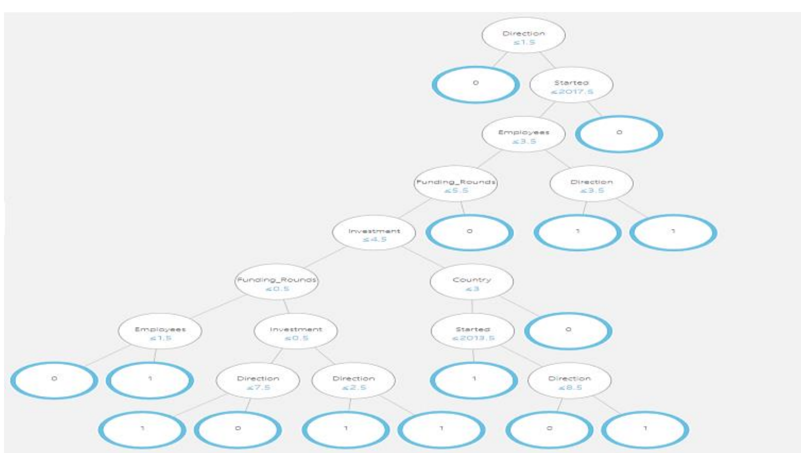

Figure 5 Decision tree for the risk factor "Inconsistency with market needs" [compiled by the author]

Figure 6 shows a decision tree for the "Competition" risk factor. The most significant criteria influencing the probability of this risk factor, such as "Area of activity", "Amount of investment", and "Funding round", were identified. The "Area of activity" factor determines the industry and market in which the innovative project will compete. If this is a highly competitive industry, then the risk of competition will be higher. The "Amount of investment" affects the competitiveness of a startup since a significant investment can enable the startup to compete with stronger players in the market. The "Investment round" factor also affects competition since later investment rounds usually signify that the startup has already achieved a certain level of success and competitiveness. The accuracy that determines the "Competition" risk factor is 80%.

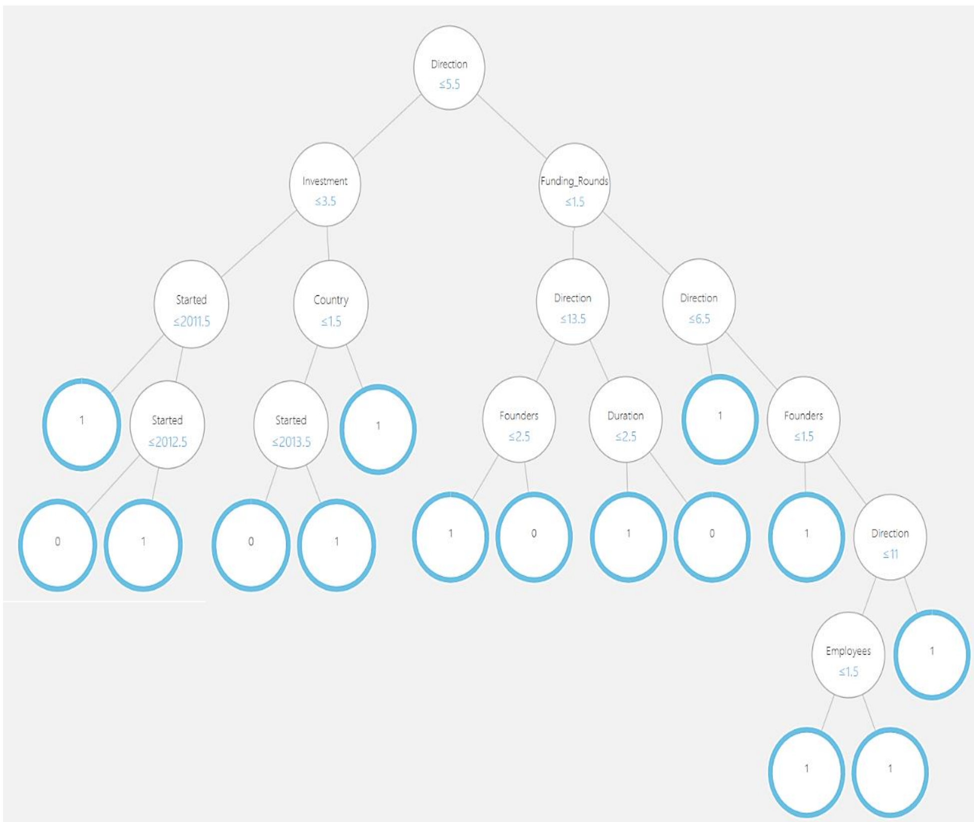

Figure 6 Decision tree for the "Competition" risk factor [compiled by the author]

Figure 7 shows a decision tree for the risk factor "Errors in choosing a business model." The criteria "Duration of the project" and "Size of investment" impact the likelihood of this risk factor occurrence. The project's duration reflects the experience and knowledge of the team that develops and implements the business model, as well as the time spent testing and debugging. The longer a team works on a project, the more likely they will implement the idea successfully. The amount of investment determines the amount of resources available to develop and implement the business model. A more significant investment allows the team to put more money into research and development, which can help them identify and fix potential problems early on. The "Round of investment" and "Area of activity" are also important criteria that influence the "Errors in choosing a business model" risk factor. The forecasting accuracy of the risk factor "Errors in choosing a business model" is 73%.

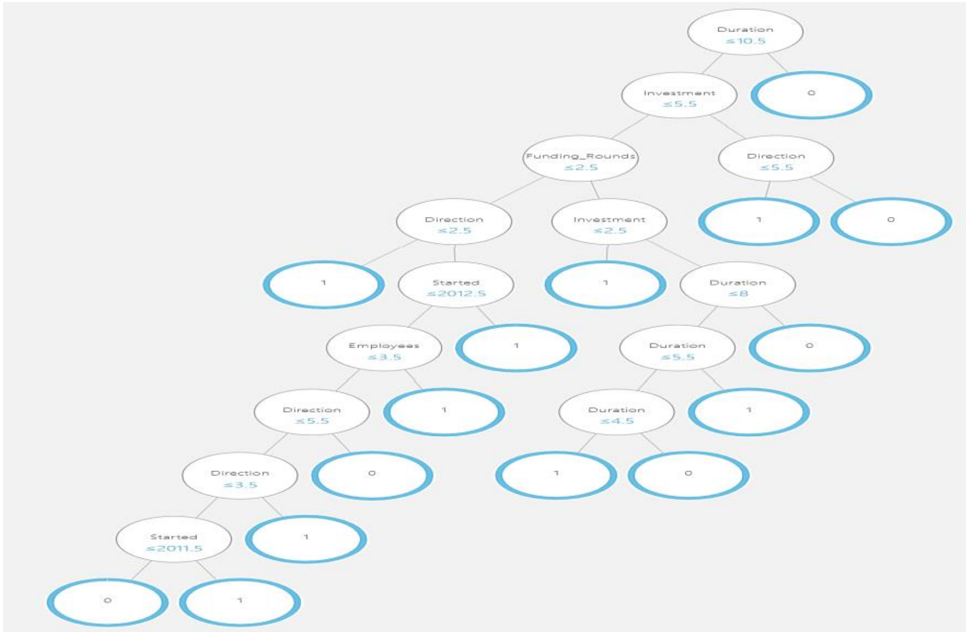

Figure 7 Decision tree for the "Errors in choosing a business model" risk factor [compiled by the author]

The decision trees presented in Figures 5-7 allow us to evaluate the logic of forecasting risk factors. As a result of the study, a matrix was compiled (see Table 2), which will enable us to assess the influence of criteria on predicting the likelihood of the occurrence of such risk factors as "Inconsistency with market needs," "Competition," and "Errors in choosing a business model".

Table 2 – Assessment of the level of influence of criteria on the likelihood of risk factor occurrence

Criterion/Risk factor	Inconsistency with market needs	Competition	Errors in choosing a business model	Level of influence
1	2	3	4	5
Area of activity	9	9	3	21
Country	1	3	0	4
Number of founders	0	1	0	1
Number of employees	3	0	1	4
Amount of investment	1	6	6	13
Funding round	1	6	3	10
Year of implementation start	6	3	1	10
Duration of project	0	1	9	10

The analysis of Table 2 shows that specific criteria significantly impact the likelihood of risk factors in innovative entrepreneurial projects. Essential criteria that can increase the likelihood of risk occurrence are "Area of activity", "Amount of investment", "Funding round", and "Duration of the project".

Thus, these criteria have the most substantial impact on the likelihood of risk occurrence in innovative entrepreneurial projects. The results of this study can be used to forecast the risks of innovative startups at the international level. The model developed in the study allows us to determine the likelihood of risk occurrence based on various criteria, such as area of business, country, number of founders, and others. This can help investors and entrepreneurs assess potential risks and make informed decisions about funding or partnering with startups.

DISCUSSION

The work is a scientific contribution to the problem under study since it is proposed to forecast risk factors in innovative business projects by building a machine-learning model. Taking into account a set of specific criteria, such as the area of activity, country, number of founders, number of employees, investment amount, investment round, start year of implementation and duration of the project, the model allows us to forecast the likelihood of potential risk factors such as inconsistency with market needs, competition and errors in choosing a business model. The model proposed by the authors is based on the methods that have shown the highest accuracy in the works of G. Ross and A. Krishna. In contrast to the authors' developments, the existing studies by G. Ross, B. Sharlichev, A. Krishna, W. Kaiser, and J. Kuhn aim to predict startup success in terms of a round of investment, the size of the investment and the survival of a startup. Those studies do not pay enough attention to forecasting risks when implementing innovative projects.

CONCLUSION

This study demonstrates the possibility of machine learning forecasting innovative entrepreneurial risk factors. The scientific novelty of this study lies in the development and justification of using a machine-learning model to analyses and predict the risks of innovative entrepreneurial projects. This process involves processing large volumes of data in real-time, obtaining a more objective risk assessment than subjective methods, and saving time and resources by automating the risk assessment. This risk forecasting model can use data on closed projects and information on successfully implemented projects, which will expand the database and increase the accuracy of the machine learning model.

Machine learning can also forecast the risks of innovative entrepreneurial projects and select projects for subsequent financing. Machine learning for predicting the risks of innovative entrepreneurial projects can significantly increase the efficiency and accuracy of decision-making. This model can be used by managers of innovative entrepreneurial projects and venture investors and in the selection and development of projects in startup studios at higher educational institutions. Further practical development of the study will be associated with using this model to forecast risks when analysing a sample, including data on innovative entrepreneurial projects that won the "Student Startup" competition.

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